Received: 20 February 2020 | Revised: 2 September 2020 | Accepted: 6 February 2021
DOI: 10.1002/for.2770

RESEARCH ARTICLE

WILEY

Human resources and corporate failure prediction modeling: Evidence from Belgium

Xavier Brédart[1] | **Eric Séverin**[2] | **David Veganzones**[3]

[1]Institut de recherche humanOrg, Université de Mons, Mons, Belgium
[2]Laboratoire Rime Lab, Université de Lille, IAE Lille, Lille, France
[3]INSEEC U Research Center, ESCE International Business School, Paris, France

Correspondence
Xavier Brédart, Institut de recherche humanOrg, Université de Mons, 17, Place Warocqué, 7000 Mons, Belgium.
Email: xavier.bredart@umons.ac.be

Abstract
This paper analyzes the prediction performance of human resources (HR) variables in corporate failure modeling. We define corporate failure as a two-phase process from financial distress to bankruptcy, so that we can determine the prediction power of HR variables along a firm's phase in the financial deterioration process. We demonstrate the use of HR variables and their application to a two-phase corporate failure model, providing first evidence for the predictive power of HR variables. The experimental results, based on real-world datasets from Belgium, show that HR variables used in conjugation with accounting-based information improve the accuracy of prediction modeling. However, the predictive power of HR variables varies in different phases of corporate failure with better prediction accuracy during the initial symptoms of corporate failure (i.e., financial distress). Findings show that our proposed model predicted financial distress with 84.1%, whereas the accuracy decreased to 83.3% when predicting bankruptcy. Besides, they also show that, on average, the inclusion of HR variables improves the global accuracy of the prediction models of 3.8% and allows to decrease Type I error of 5%.

KEYWORDS
bankruptcy, corporate failure, forecasting, human resources

1 | INTRODUCTION

Although bankruptcies in Organisation for Economic Co-operation and Development affiliated countries peaked in 2009, the number of firms filing for bankruptcy annually remains high. The economic, social, and personal costs of these failures are significant; thus, corporate failure is a crucial topic in corporate finance, and detecting it is important for decision-making processes in many sectors (e.g., banks and rating agencies).

Therefore, many corporate failure and bankruptcy prediction models have been created since beaver's pioneer study in 1966. Modeling techniques may vary from statistical methods (Altman, 1968; Ohlson, 1980) to artificial intelligence methods (Kim & Kang, 2010; Tang, Li, Tan, & Shi, 2020) or ensemble methods (Kainulainen et al., 2014). Nevertheless, most studies refer to financial information because data are standardized and available. However, several authors (e.g., du Jardin, 2012) contest the idea that models employing only financial ratios are the most accurate and extend detection models to include nonfinancial variables. These variables can be quantitative or qualitative and either firm-specific such as market valuation (Campbell, Hilscher, & Szilagyi, 2008; Shumway, 2001; Tian, Yu, & Guo, 2015), corporate governance (Ciampi, 2015; Daily & Dalton, 1994), or relational (Tobback, Bellotti, Moeyersoms, Stankova, & Martens, 2017) data or refer to the economic environment, such as market share (Becchetti & Sierra, 2003).

The resulting forecasts are typically more accurate than those estimated with only financial ratios.

Because including nonfinancial variables with financial information can account for more causes that lead to firm failure and thus better predict failure, questions may arise about the extent to which human resources (HR) variables can influence corporate failure prediction modeling. HR constitutes an important, specific feature for all types of firms in terms of costs, strategic resources, and competitive advantages (Theriou & Chatzoglou, 2008). Since Chaganti, Mahajan, and Sharma's (1985) seminal study, many studies (Ciampi, 2015; Daily & Dalton, 1994; Donoher, 2004; Hambrick & D'Aveni, 1988, 1992; Lajili & Zéghal, 2010; Platt & Platt, 2012) have been devoted to the link between business failure and corporate governance. These studies especially include, in business failure prediction models, variables reflecting top management teams characteristics such as board size, board independence, or CEO duality. These studies report that some top-management configurations do matter as business failure is analyzed.

Top management teams refer to managerial aspects of firms and only represent a small part of the total HR in businesses. Other HR dimensions are reported into firms' social statements; they reflect operational aspects of firms. We argue that this information should be taken into consideration for corporate failure modeling.

To the best of our knowledge, this question has not been tackled yet in the academic literature. Because HR decisions are important for the development and execution of firms' strategic business plans (Huselid, 1995) and competitive strategies (Barney, Ketchen, & Wright, 2011), HR management (HRM) practices can become a source of sustained competitive advantage (Porter, 1985) and positively influence performance outcomes (Crook, Ketchen, Combs, & Todd, 2008). Therefore, HRM influences employees' motivation, skills, and productivity as key components of value creation, which increases operating performance and ultimately translates into better financial performance (Becker, Huselid, Pickus, & Spratt, 1997; Dyer & Reeves, 1995; Huselid, 1995). As Bendickson and Chandler (2019) documented, effective HRM is a key determinant of organizational performance and positively associated with financial performance.

Therefore, managing this resource provides a relevant framework for explaining corporate growth and failure (Rauch & Rijsdijk, 2013). In this study, we use information outsourced from social statements that Belgian firms are required to publish. This information allowed us to compute an initial set of 48 static and dynamic variables reflecting HR characteristics up to 2 years before failure. We further classify computed variables as per Huselid's (1995) four dimensions of HRM practices: employee recruitment and selection procedures (e.g., proportion of permanent working contracts) compensation and performance management systems (e.g., cost of labor per hour), employee involvement (e.g., working hours per worker), and employee training (e.g., number training hours/average number of workers). We further use a three-phase variable selection process on both financial ratios and HR variables to ensure model parsimony.

Based on Belgian datasets, this study contributes to the corporate failure prediction literature in several ways. First, although the relationship between HR and a firm's performance is well established (Combs, Liu, Hall, & Ketchen, 2006; Gong, Law, Chang, & Xin, 2009), to the best of our knowledge, we are the first to use data from the social reports of companies to predict corporate failure. Our study identifies the best combination of HR variables and financial ratios to build more accurate corporate failure models.

Second, extant literature does not analyze all phases of the corporate failure process, and explanatory variables might have different effects. Therefore, we use two datasets marked by distinct stages of corporate failure to analyze the prediction power of HR variables. Specifically, we contribute to the performance of the prediction model by using HR variables that occur at different phases of a firm's financial deterioration, from financial distress to bankruptcy. We present a threshold model to analyze HR characteristics as a potential driver in corporate failure models. Third, we investigate the relevance of explanatory variables in corporate failure prediction models. Our results reveal that the inclusion of HR variables in prediction models significantly improves modeling accuracy. Nevertheless, the relevance of HR variables depends on a firm's degree of financial distress. Using an indicator of profitability to apprehend corporate failure, we observe that models considering failed firms with a high magnitude of distress are more affected by HR variables than models considering failed firms with a low level of distress.

This paper is organized as follows: in Section 2, we present the literature review on business failure prediction, in Section 3, we describe the research methodology, and in Section 4, we present and discuss the results. Section 5 concludes with study limitations and suggestions for further research.

2 | LITERATURE REVIEW

For more than 60 years, researchers have built corporate bankruptcy models using various prediction methods.

Beaver (1966) pioneered corporate failure models in a study that involved discriminant analysis of a single financial ratio (i.e., cash flow to total debt). Altman (1968), Ohlson (1980), and Zmijewski (1984) suggest statistical methods that use well-known concepts from statistical decision theory to establish discriminatory boundaries between two firm classes: failed and nonfailed. These studies represent the initial corporate failure models that rely on statistical financial information, which was established as the main predictor of corporate failure. However, these statistical methods are limited, in that they depend on restrictive data assumptions (Balcaen & Ooghe, 2006).

With the advent of computer sciences, authors have also proposed artificial intelligence methods such as neural networks (NN) (Kim & Kang, 2010; Tang, Li, Tan, & Shi, 2020; Yang, Platt, & Platt, 1999) and genetic algorithms (Gordini, 2014; Shin & Lee, 2002) for corporate failure prediction modeling. Compared with statistical methods, artificial intelligence methods can learn directly from the data and model more complex nonlinear functions, which enables researchers to predict corporate failure more effectively. Another recent trend uses ensemble methods and combines multiple prediction approaches, reflecting the idea that properly combining several diverse independent prediction methods into one classification output provides better results than a single prediction method (Kainulainen et al., 2014).

However, no consensus has emerged regarding the potential superiority of one prediction method to others, as detailed in Balcaen and Ooghe's (2004) comprehensive analysis of performance bankruptcy prediction methods. Consequently, a new perspective proposes that the performance of corporate failure models depends on more than the complexity of the prediction method, and recent advances focus on investigating novel explanatory variables and the extent to which they influence the performance of corporate failure models.

Most corporate failure models are designed with financial ratios, in the form of static (i.e., calculated for a particular year) (Farooq & Qamar, 2019; Lohmann & Ohliger, 2019) or dynamic (i.e., variation over several years) (Heo & Yang, 2014; Shin, Lee, & Kim, 2005) indicators. These variables are objective measures based on the publicly available information (Micha, 1984) and have achieved a dominant position as predictors. They have widely been used ever since Beaver (1966) asserted that financial ratios contain valuable information about corporate failure and have the power to predict bankruptcy.

Nevertheless, Argenti (1976) argued that financial ratios become less reliable as failure approaches because the failing company's management may have recourse to "creative accounting" practices used by the failing company's management aiming to hide the real financial condition of the firm. Moreover, it has been argued (Argenti, 1976; du Jardin, 2012) that models employing relevant nonfinancial variables (considered as less open to manipulation) in combination with financial ratios result in more accurate predictions. Keasey and Watson (1987), in the context of small companies, investigated the prediction accuracy of a model including nonfinancial variables in addition to financial ratios. These nonfinancial variables concern topics such as the management structure or the manipulation of accounting information. Their study concluded that the model including nonfinancial variables provides marginally better predictions than the model with financial ratios only. Laitinen (1999) used filed information from a credit information agency. Arppe et al. (2005) argued that the textual contents of the quarterly reports contain important information that is further reflected in the financial data of the company. Campbell, Hilscher, and Szilagyi (2008), Shumway (2001), and Tian, Yu, and Guo (2015) added market valuation information to their models, which allowed them to significantly improve the accuracy of their models. They also report that the predicting power of the market variables decreases as the event of failure approaches. Laitinen (2008) assesses the probability of failure in reorganization building a model including pre-filing nonfinancial information such as industry branch, location or court, age of the firm and entrepreneur, number and gender of entrepreneurs, number of board members, or auditor competence. Altman, Sabato, and Wilson (2010) reported that the use of event (such as whether the firm is late to file its financial statements), audit, and firm-characteristic data to predict the probability of corporate failure of unlisted firms makes a significant contribution to increasing the default prediction power of risk models. In their prediction model, Pervan and Kuvek (2013) used, in addition to financial ratios, firm characteristics such as the number of employees, the quality of accounting information, the dependence on key customers, the firm owners' personal credit performance, and the management quality and reported an increase in the prediction accuracy.

Ciampi (2015) analyzed the relationship between corporate governance mechanisms and business failure in small enterprises (SE). He applied a logistic regression to a sample of 934 Italian small enterprises and compared the prediction accuracy of a model made of financial ratios only and a second model including both financial and nonfinancial (reflecting governance mechanisms) variables. The results of his study are as follows: (i) CEO duality, owners' concentration, and a small proportion of outside directors within the board are significantly and negatively correlated with business failure and (ii) governance variables improve the accuracy rates of the SE's default forecasts. Altman, Iwanicz-Drozdowska, Laitinen, and Suvas (2016) built a financial distress prediction model in the Finnish environment. They showed that nonfinancial measures such as the environmental risk, the payment behavior, and the board member characteristics can be significant predictors of bankruptcies and that nonfinancial variables may be significant predictors for as long as several years and, finally, that the most accurate long-range prediction results combine financial and nonfinancial variables.

The inclusion into prediction models of nonfinancial variables allows to increase their prediction accuracy. Although many variables have already been tested, regarding the human potential of firms, it seems that only top management teams have been investigated. To the best of our knowledge, this study is the first to investigate the impact of the inclusion of nonfinancial variables related to Human Resources on the accuracy of failure prediction models.

3 | RESEARCH METHODOLOGY

3.1 | Data and methodology

We gathered data from the Bureau van Dijk Bel-First database, including social statements and financial information about Belgian firms. We built the dataset in three stages. First, we established the definition of corporate failure. Corporate failure represents a dynamic process in which the initial condition of a firm changes over time until it ends in bankruptcy. According to Sun, Li, Huang, and He (2014), the first sign of corporate failure occurs when firms begin to experience financial distress—that is, when firms encounter a situation in which they experience difficulties fulfilling their obligations. Under this circumstance, firms should be able to adapt their internal procedures to mitigate the risk and avoid bankruptcy. Bendickson and Chandler (2019) documented that the successful adjustment of the uses of organizational resources is central to a firm's survival. The effect of HR variables in the initial steps of the failure process is observable, and changes in the internal organizational structure may act as a buffer to protect a firm from bankruptcy. Therefore, we consider the criterion of Balcaen, Manigart, and Ooghe (2011), who defined financial distress as a firm with negative recurring profit after taxes over a year; we add the stipulation that this negative profit occurs for two consecutive years. This definition indicates a firm's efficiency and success and the first signs of failure. Second, we selected nonlisted firms with at least 20 employees because, as per the Belgian law, they are required to publish HR information. Third, we extracted annual accounts, income statements, and HR information from these samples. Our dataset includes 500 failed firms that fulfilled this criterion from 2015 to 2017. We then randomly matched these firms with nonfailed firms[1] to ensure they reflected the same proportion and characteristics as failed firms. The resulting dataset contained 1000 firms (i.e., 500 failed and 500 nonfailed firms).

Finally, our database contains financial variables for Belgian firms but also HR variables build upon information outsourced from social statements. Social statements include information that encompasses Huselid's (1995) four dimensions of HRM practices: employee recruitment and selection procedures, compensation and performance management systems, employee involvement, and employee training.

3.2 | Prediction methods

3.2.1 | Logistic regression

Logistic regression (LR), proposed by Ohlson (1980), models a binary decision (i.e., output) by estimating the posterior probabilities of the classes according to the linear functions of the independent variables. An LR creates a discrimination score (z-score) to distinguish two variables by using the nonlinear maximum likelihood. LR is defined as follows:

$$z = \frac{1}{1 + e^{-(w_0 + w_i x_i)}}, \tag{1}$$

where x_i are explanatory variables, w_i are the weights estimated using maximum likelihood estimation, and z is the score for a given firm.

3.2.2 | Support vector machine

Support vector machine (SVM) was introduced by Boser, Guyon, and Vapnik (1992) for data classification. An SVM transforms the input vector into a higher dimensional space (i.e., kernel trick) that contains a separating hyperplane with a maximal margin. Then, this model provides a linear discriminant function based on a margin maximization condition that increases the separation between classes. An SVM builds the hyperplane separation between classes as follows:

$$\mathrm{MIN}_{w,b,e}\frac{1}{2}w^t w+C\sum_{i=1}^{N}e_i, \tag{2}$$

$$\text{subject to}\, y_i(w\varphi(x_i)+b)+e_i-1\geq 0\, e_i\geq 0, \tag{3}$$

where φ (x_i) maps training vectors onto a high-dimensional space, w is the weight vector, b is the bias term, C is the penalty for the error, and e_i is the slack variable (Vapnik, 1998).

Then, a classification decision is given as follows:

$$f(y)=\mathrm{sign}\left(\sum_{i=1}^{N}y_i p_i K(x,x_i)+b\right), \tag{4}$$

where *sign* is the sign function, p_i is the parameter, K is the function, and $K(x, x_i) = \exp(-\delta|x_i - x_j|^2)$ is the kernel radial basis function.

3.2.3 | Neural networks

NN, first applied to corporate failure by Messier and Hansen (1988), models a nonlinear functional mapping between a set of input variables and a set of output variables. Our NN prototype consists of three layers: an input layer with n neurons input variable, an output layer with two responses (failed and nonfailed), and a hidden layer with m neurons that is connected with the input and output layers. NN compute a z score, the failure probability of a given firm, as follows:

$$z=g\left(\sum_{J=0}^{M}w_{kj}g\left(\sum_{i=0}^{d}w_{ji}x_i\right)\right), \tag{5}$$

where g is the activation function, x_i are explanatory variables, w_{ji} corresponds to the weight matrix including the bias term between the input node (i) and the hidden node (j), and w_{kj} corresponds to the weight matrix with bias connecting the hidden node with the output layer.

3.2.4 | Decision trees

Decision tree (DT) models use recursive partitioning to divide the dataset according to a single variable at each level. For our model, we select the classification and regression tree (CART) algorithm introduced by Breiman, Friedman, Stone, and Olshen (1984). The CART algorithm models a binary tree that recursively partitions the predictor space with the nodes of the tree corresponding to a distinct region of the partition. That is, each observation is assigned to a specific node in which the output conditional distribution is determined.

3.2.5 | Extreme learning machine

The extreme learning machine (ELM), introduced by Huang, Zhu, and Siew (2006), models a single hidden layer feed forward NN using the random initialization of the bias and weights between the input and hidden layers. This procedure becomes ELM in an extremely fast algorithm because of the reduction in training requirements.

Considering a set of N distinct samples (x_i, y_i), $1 \leq i \leq N$, with $x_i \in \mathrm{R}^d$ and $y_i \in \mathrm{R}^c$; β_j as output weights; f as activation function; and w_j and b_j as random initialized input weights and bias, respectively, we can define ELM as follows:

$$\sum_{j=1}^{n}\beta_j f\left(w_j x_i+b_j\right)=y_i, i\in[1,N], \tag{6}$$

which can be written as $H\beta = Y$, with $\beta = (\beta_1, ..., \beta_m)^T$ and $Y=\left(y_1^T,...,y_N^T\right)^T$

$$H=\begin{pmatrix} f(w_1x_1+b_1) & \cdots & f(w_mx_1+b_m)\\ \vdots & \ddots & \vdots\\ f(w_1x_N+b_1) & \cdots & f(w_mx_N+b_m)\end{pmatrix}. \tag{7}$$

The output weights β from the hidden layer H and true outputs Y are computed by means of the Moore–Penrose generalized inverse of the matrix H, H^+ (Rao & Mitra, 1971).

3.3 | Variables

We employ two groups of explanatory variables: financial ratios and HR variables. Financial ratios represent the primary variables used to design corporate failure prediction models because they are objective, standardized, and found in accounting regulatory frameworks (Micha, 1984). Furthermore, they accurately describe firms' financial situations. We computed 50 financial ratios from the gathered annual accounts and financial statements (Table 1), relying on the ratios with corroborated power to predict corporate failure (du Jardin, 2015). At least five of the ratios pertain to the firms' financial dimensions: liquidity, financial structure, solvency, profitability, activity, and turnover.

TABLE 1 Initial set of financial ratios

Activity	
Cash flow/total sales	CF/TS
Cash flow/value added	CF/VA
EBIT/value added	EBIT/VA
EBITDA/total sales	EBITDA/TS
Gross trading profit/total sales	GTP/TS
Net income/total sales	NI/TS
Net income/value added	NI/VA
Value added/fixed assets	VA/FA
Value added/total assets	VA/TA
Value added/total sales	VA/TS
Profitability	
Cash flow/shareholder funds	CF/SF
Cash flow/total assets	CF/TA
EBIT/shareholder funds	EBIT/SF
EBIT/total assets	EBIT/TA
EBITDA/permanent equity	EBITDA/PE
EBITDA/total assets	EBITDA/TA
Net income/shareholder funds	NI/SF
Net income/total assets	NI/TA
Profit before tax/shareholders funds	PBT/SF
Financial structure	
Long term debt/shareholders funds	LTD/SF
Long term debt/total assets	LTD/TA
Net op. work capital/total assets	NOWC/TA
Shareholder funds/permanent equity	SF/PE
Shareholder funds/total assets	SF/TA
Total debt/shareholder funds	TD/SF
Total debts/total assets	TD/TA
Liquidity	
(Cash + mark. sec.)/current liabilities	(C + MS)/CL
(Cash + mark. sec.)/total sales	(C + MS)/TS
Cash/current assets	C/CA
Cash/total assets	C/TA
Current assets/current liabilities	CA/CL
Current assets/total assets	CA/TA
Current liabilities/total assets	CL/TA
Current liabilities/total sales	CL/TS
Inventories/total assets	I/TA
Quick assets/current liabilities	QA/CL
Quick assets/total assets	QA/TA
Working capital/total assets	WC/TA
Working capital/total sales	WC/TS
Solvency	
Financial debts/cash flow	FD/CF
Financial expenses/EBITDA	FE/EBITDA
Financial expenses/net income	FE/NI
Financial expenses/total assets	FE/TA
Financial expenses/value added	FE/VA
Turnover	
Accounts payable/total sales	AC/TS
Current assets/total sales	CA/TS
Inventories/total sales	I/TS
Net op. work. capital/total sales	NOWC/TS
Receivables/total sales	R/TS
Total sales/total assets	TS/TA

Abbreviations: EBIT, earnings before interest and taxes; EBITDA, earnings before interest, taxes, depreciation, and amortization; mark. sec., marketable securities; net op. work. capital, net operating working capital.
Source: du Jardin (2015).

This set includes too many variables to build a model; thus, we select variables carefully to ensure model parsimony and maintain accuracy and generalizability. Therefore, we verified the significant differences in means and medians between failed and nonfailed firms' financial ratios using *t*-tests and Kruskal–Wallis tests to determine whether they provided information that distinguished between classes. Because many variables share a common numerator or denominator, they might exhibit high correlations. Thus, we used variance inflation factor to check for multicollinearity between independent variables in the model to avoid redundancy. Kim, Kang, and Kim (2015) showed that a variable with a variance inflation factor equal to or higher than four signifies multicollinearity; thus, we eliminated these variables.

Finally, a three-phase variable selection processed the features as follows: first, we selected four variable selection methods that have been applied in bankruptcy prediction literature: (1) stepwise search with Wilks's lambda as stopping criterion, (2) stepwise search with chi-square as stopping criterion, (3) genetic algorithm, and (4) particle swarm optimization. Second, we drew 200 random bootstrap samples from the training set and applied each selection method to make the variable selections. Third, following du Jardin (2012) and Ciampi, Cillo, and Fiano (2018), we used only the variables that appear in 70% of the bootstrap samples and are selected by at least three methods to build the corporate failure prediction model. The purpose of this variable selection procedure is to select the more representative features and minimize any influence of variable selection methods on the discriminatory power of the model.

TABLE 2 Initial set of HR variables

HR practices	Variables
Compensation	Benefits in addition to salary per worker $t-1$
	Benefits in addition to salary per worker $t-2$
	Cost of labor per hour of male workers
	Cost of labor per hour $t-1$
	Cost of labor per hour $t-2$
	Cost of labor per worker $t-1$
	Cost of labor per worker $t-2$
	Variation in benefits in addition to salary per worker between $t-2$ and $t-1$
	Variation in cost of labor per hour between $t-2$ and $t-1$
	Variation in cost of labor per worker between $t-2$ and $t-1$
Involvement	Variation in working hours per worker between $t-2$ and $t-1$
	Working hours per worker $t-1$
	Working hours per worker $t-2$
Recruitment	Downsizing (proportion of workers laid off) $t-1$
	Downsizing (proportion of workers laid off) $t-2$
	Ln (number of workers)
	Proportion of end of working contract (not downsizing) $t-1$
	Proportion of end of working contract (not downsizing) $t-2$
	Proportion of female workers $t-1$
	Proportion of female workers $t-2$
	Proportion of fixed-term working contracts $t-1$
	Proportion of fixed-term working contracts $t-2$
	Proportion of male workers $t-1$
	Proportion of male workers $t-2$
	Proportion of permanent working contracts $t-1$
	Proportion of permanent working contracts $t-2$
	Variation in downsizing between $t-2$ and $t-1$
	Variation in proportion of end of working contract between $t-2$ and $t-1$
	Variation in proportion of fixed-term working contracts between $t-2$ and $t-1$
	Variation in proportion of permanent working contracts between $t-2$ and $t-1$
	Variation in proportion of female workers between $t-2$ and $t-1$
	Variation in proportion of male workers between $t-2$ and $t-1$
Training	(Number training hours/average number of female workers) $t-1$
	(Number training hours/average number of female workers) $t-2$
	(Number training hours/average number of male workers) $t-1$
	(Number training hours/average number of male workers) $t-2$
	(Number training hours/average number of workers) $t-1$
	(Number training hours/average number of workers) $t-2$
	Cost of training per hour $t-1$
	Cost of training per hour $t-2$
	Number of training hours/total number of working hours $t-1$
	Number of training hours/total number of working hours $t-2$
	Variation (number training hours/average number of female workers) between $t-2$ and $t-1$
	Variation (number training hours/average number of male workers) between $t-2$ and $t-1$
	Variation (number training hours/average number of workers) between $t-2$ and $t-1$
	Variation in cost of training per hour between $t-2$ and $t-1$
	Variation (number of training hours/total number of working hours) between $t-2$ and $t-1$

Note: Year t refers to the year when failure has been recorded.
Abbreviation: HR, human resources.

Moreover, we computed 48 static and dynamic variables reflecting HR characteristics (Table 2). These variables encompass Huselid's (1995) four dimensions of HRM practices: employee recruitment and selection procedures, compensation and performance management systems, employee involvement, and employee training. We considered ratios for the year before the failure date (i.e., year $t - 1$), 2 years before (i.e., year $t - 2$), and the variation between periods. To test the impact of HR information in corporate failure models, we also selected relevant variables. We followed the same three-phase variable selection process to select the relevant HR variables.

Table 3 presents the financial and HR selected variables.[2] The selected financial ratios represent all the financial dimensions, which might encompass more informative data to effectively predict corporate failure. The selected HR variables represent two important dimensions of HR that can influence productivity and, consequently, firm failure: employee training and employee recruitment. Employee training contributes to the development of the human capital of the firm, which in turn positively influences firm productivity because workers acquire new or improved skills and their satisfaction increases (Harel & Tzafrir, 1999). Thus, there is a positive relationship between training activities and corporate performance. Employee recruitment, including job security, affects employees' willingness to improve firm productivity. Firms with a large proportion of permanent employment contracts are more prone to benefit from this commitment (Addessi, 2014). Thus, permanent contracts may be closely related to a firm's performance. Moreover, it is likely that firms in financial distress show different measures of structural organization than nonfailed firms. Specifically, our variable selection procedure reports that the average number of training hours per employee and the proportion of permanent employees at the firm are important to firm failure rates.

TABLE 3 Selected variables

Financial ratios	HR variables
Quick assets/current liabilities	(Number training hours/average number of workers) year t (HR1)
Financial debt/cash flow	Proportion of permanent working contracts year t (HR2)
EBITDA/permanent equity	
Long term debt/total assets	
EBIT/value added	
Total sales/total assets	

Abbreviations: EBIT, earnings before interest and taxes; EBITDA, earnings before interest, taxes, depreciation, and amortization; HR, human resources.

4 | RESULTS

4.1 | Prediction performance using HR variables

This study investigates the role of HR variables on the likelihood of a firm's failure and whether HR variables provide significant information to predict failure. We thus compare the results of a traditional corporate failure model with our proposed model that includes HR variables. We computed four models: a traditional model that relies solely on financial ratios (Model A) and others that rely on HR variables in combination with financial information (Models B, C, and D).

We applied these models to five classifiers: the LR, the SVM, the NN, the DT, and the ELM. Although the LR requires no specific settings, we conducted parameter optimization for the other four methods by using cross-validated trials. To design a tree, we used the CART algorithm (Breiman, Friedman, Stone, & Olshen, 1984). The tree was pruned to the best size through the process of cross-validation. For the NN, the cross-validated trials selected the best-performing number of hidden neurons in a predefined range of 10 to 30 neurons, and a single hidden layer NN was chosen with the Levenberg–Marquardt algorithm as the optimization technique and the hyperbolic tangent as an activation function. We built the SVM using the radial-basis kernel, which requires two parameters to optimize: the regularization parameter, C, set as a value between 10 and 100 and the parameter of the radial basis function, p, set as a value between 1 and 25. For the ELM, only the size of the hidden layer needs to be set, which matches the range of the NN. For the tests, we ran model estimations and obtained firm classification prediction rates for 200 randomized tenfold cross-validation.

We explored the performance of these models using the three evaluation metrics commonly applied in financial experiments: accuracy, which measures overall performance, and type I and type II errors, which evaluate the misclassification of failed firms and nonfailed firms, respectively. Panel A of Table 4 indicates the average classification, with the significant differences listed in Panel B.

The results indicate that HR variables can predict corporate failure, and HR choices provide valuable information about a firm's financial condition. This result is not completely surprising; extant literature has documented a relationship between HR choices and firm performance (Bendickson & Chandler, 2019; Oh, Kim, & Van Iddekinge, 2015) that might explain why this rather specific information is relevant to distinguish between failed and nonfailed firms.

TABLE 4 Classification rate and significant differences (%)

		Panel A: Classification rate (%)				Panel B: Significant differences		
		Model A	Model B	Model C	Model D	Model A–B	Model A–C	Model A–D
LR	Acc.	80.7	81.6	83.1	84.6	-	-	**
	Ty-I	21.1	19.3	18.4	16.6	-	-	**
	Ty-II	17.6	17.4	15.4	14.3	-	-	**
SVM	Acc.	80.7	82.0	83.5	84.5	-	*	**
	Ty-I	21.7	19.5	18.2	16.7	-	**	***
	Ty-II	16.9	16.5	14.8	14.5	-	-	-
NN	Acc.	79.5	81.4	82.1	83.5	-	-	**
	Ty-I	21.1	18.9	17.4	16.3	-	**	***
	Ty-II	19.9	18.4	18.4	16.7	-	-	*
DT	Acc.	80.4	81.8	83.2	84.2	-	-	**
	Ty-I	21.5	19.9	17.4	15.8	-	**	***
	Ty-II	17.7	16.5	16.2	15.8	-	-	-
ELM	Acc.	80.0	81.2	82.6	83.6	-	-	**
	Ty-I	21.4	20.1	17.0	16.1	-	**	***
	Ty-II	18.6	17.5	17.8	16.7	-	-	-

Note: Model A is built solely on financial ratios, Model B is built on financial ratios and HR1, Model C is built on financial ratios and HR2, and Model D is built on financial ratios and both HR variables. Acc. refers to the global accuracy of the model, Ty-I is the percentage of type I errors, and Ty-II is the percentage of type II errors. Significant levels are calculated using proportion tests.

***1%.

**5%.

*10%.

However, our results also indicate discrepancies in the predictive capabilities of these variables. When we compare the accuracy rates from Model A (i.e., financial ratios) with Model B (i.e., financial ratios and the HR1 variable), the global accuracy increases from 80.3% to 81.6%, whereas with Model C (i.e., financial ratios and the HR2 variable), an 82.9% accuracy rate is achieved. Although HR-based models are more accurate than the traditional model, the HR indicators individually do not present enough prediction power to significantly improve the performance. Nonetheless, the inclusion of both HR indicators together with financial ratios exhibits high discriminatory power; Model D is significantly more accurate than the traditional model (i.e., an improvement of 3.8%; p value = .026).

To better explain these initial results, we analyze the classification errors. The models using HR variables substantially improve the prediction classification of failed firms. The traditional model (Model A) achieved an average type I error rate of 21.4%, whereas the HR-based models obtained an average type I error rate of 17.8% (significant at the 5% level). Nonetheless, this improvement is completely different between the two HR variables. Although Model B exhibits some improvement in the capacity to identify failed firms compared with the traditional model, those differences are not statistically significant. The HR2 variable (Model C) provides relevant complementary information that enables statistically significant differences (i.e., four of five cases). By contrast, none of the HR variables seem to affect the prediction of nonfailed firms; that is, of the 20 different type II errors calculated, none are statistically significant. It is relevant to group the two HR variables alongside financial ratios (Model D). Although the predictive power of individual HR variables is not negligible (especially HR2), the model that aggregates both variables reports remarkable predictive power compared with the traditional financial ratios-based model.

The results show that the effects of HR variables are more pronounced for failed firms. Nonetheless, we might speculate that experiencing financial distress is a necessary but insufficient condition to cause a firm to adapt its internal structure; therefore, it is the magnitude of financial distress that forces a firm to adopt new measures. Whether to reverse a trend or to ensure day-to-day management during financial distress, firms with a high magnitude of financial distress might demonstrate different organizational structures than firms experiencing a smaller magnitude of financial distress. From an HR standpoint, adjustments to the workforce often involve staff reductions but can also affect other facets of HRM (Santana, Valle, & Galan, 2017) such as training expenses or types of employment contracts (i.e., permanent vs. fixed-term contracts). This might explain why those variables are especially relevant in predicting failed firms.

4.2 | Additional analysis

Because the effect of HR variables should have different weights according to the degree of financial distress, we carried out further predictions to understand the capacity of HR variables to predict a firm's degree of financial distress. Thus, we followed Hansen's (2000) procedure to construct intervals by inverting the likelihood ratio statistic that yields to asymptotically conservative confidence regions. We use a threshold model to split asymptotically the failed samples according to their degree of financial distress. This model calculates a threshold of a predefined variable (i.e., degree of financial distress) that splits the sample into groups (known as regimes). The two-stage threshold is defined as follows[3]:

$$Y_t = \begin{cases} \emptyset_0^{(1)} + \emptyset^{(1)} X_t + \varepsilon_t^{(1)} \; if \; Z_t \leq s \\ \emptyset_0^{(2)} + \emptyset^{(2)} X_t + \varepsilon_t^{(2)} \; if \; Z_t > s \end{cases}, \tag{8}$$

where $\varepsilon_t^{(j)}$, $j = 1, 2$, $t = 1, ..., n$, are two white noises independent of variance $\sigma^2_{(j)}$ and n is the number of observations; $X_t = (Y_{t-1}, ..., Y_{t-1}, V_1, ..., V_k)'$; and $\emptyset^{(j)} = \left(\emptyset_1^{(j)}, ..., \emptyset_m^{(j)}\right)$, where $m = p+k$. The V_i,$i = 1$,...,k, are explanatory variables. Finally, Z_t and s represent the threshold variable and location parameter, respectively.

The threshold variable is based on the revised z score developed by Altman (2000) that indicates the level of financial distress (Appendix B).[4] The application of this model generates two regimes, one that represents failed firms with a high magnitude of distress (i.e., Regime 1, below the threshold value, includes 195 firms) and one that includes failed firms with a low level of distress (i.e., Regime 2, above the threshold value, includes 305 firms).

Table 5 identifies the classification rates of failed firms within the two regimes. The increase of accuracy from Model A to models with HR variables (Models B, C, and D) is more pronounced for failed firms with high magnitudes of distress (Regime 1). This means that the HR variables (i.e., the average number of training hours per employee and the proportion of permanent workers in the firm) are more discriminant for failed firms with high magnitudes of distress. These important differences in HR variable measurements may be symptoms of more advanced stages of corporate failure or the consequences of adapting to the internal organizational structure induced by the precarious situation of the firms. That is, the magnitude of financial distress may force firms to adopt organizational measures affecting HRM. These results are not unexpected because firms with a high magnitude of distress might adapt their organizational structures to reverse the trend or ensure the stability of day-to-day management during the financial distress situation by, for example, reducing costs linked to training or opting for a more flexible recruitment policy.

4.3 | Further evaluation

Previous results have highlighted the role of HR variables in the initial stages of firm failure (i.e., when firms experience financial distress). However, to evaluate whether these variables enhance the performance of corporate failure models, it is essential to address the model's capacity to identify firms close to the final stage of corporate failure, bankruptcy. Therefore, we built a new

TABLE 5 Correct classification rates of failed firms and significant differences between the two regimes (%)

	Panel A: Classification rate (%)								Panel B: Significant differences					
	Model A		Model B		Model C		Model D		Model A–B		Model A–C		Model A–D	
	Reg.1	Reg.2	Reg.1	Reg.2	Reg.1	Reg.2	Reg.1	Reg.2	Reg.1	Reg.2	Reg.1	Reg.2	Reg.1	Reg.2
LR	80	78	84.6	78	86.2	78.7	89.2	79.7	*	-	**	-	***	-
SVM	83.6	74.7	87.2	76	90.2	76.4	92.3	77.7	-	-	***	-	***	-
NN	81	77.7	85.1	78.6	86.2	78.6	90.7	79.7	-	-	**	-	***	-
DT	78	76.7	82	76.7	87.2	77.7	89.7	79	-	-	***	-	***	-
ELM	80	77.7	82.5	78.4	88.2	79.7	91.3	79.3	-	-	***	-	***	-

Note: Models A–D as defined in Table 4. Reg.1 refers to Regime 1 and reg.2 refers to Regime 2. Significant levels are calculated using proportion tests.

***1%.

**5%.

*10%.

TABLE 6 Classification rate and significant differences (%)

		Model A	Model B	Model C	Model D	Model A–B	Model A–C	Model A–D
LR	Acc.	76.7	78.9	80.7	81.9	-	-	*
	Ty-I	25.0	22.9	16.9	16.9	-	***	***
	Ty-II	21.6	19.3	21.6	19.9	-	-	-
SVM	Acc.	77.9	79.5	81.7	82.9	-	-	*
	Ty-I	23.6	23.6	16.2	16.4	-	***	***
	Ty-II	20.6	17.4	20.4	17.8	-	-	-
NN	Acc.	82.4	83.1	85.1	85.2	-	-	-
	Ty-I	18.2	18.3	14.6	14.5	-	-	-
	Ty-II	16.9	15.6	15.0	15.0	-	-	-
DT	Acc.	78.6	79.9	81.7	83.5	-	-	*
	Ty-I	24.0	22.2	18.4	16.0	-	**	***
	Ty-II	18.8	18.0	18.2	17.0	-	-	-
ELM	Acc.	80.0	81.6	82.1	82.9	-	-	-
	Ty-I	21.5	19.1	17.0	16.0	-	*	**
	Ty-II	18.5	17.7	18.8	18.2	-	-	-

Note: Models A–D as defined in Table 4. Acc. refers to the global accuracy of the model, Ty-I is the percentage of type I errors, and Ty-II is the percentage of type II errors. Significant levels are calculated using proportion tests.

***1%.

**5%.

*10%.

dataset following the same stages as previous. We identified 210 firms that went bankrupt (i.e., they were liquidated or reorganized between 2015 and 2017). Then, we randomly paired them with nonbankrupt firms. Our final dataset consists of 420 firms with an equal proportion of bankrupt and nonbankrupt firms.

The results in Table 6 align with previous findings. The global accuracy of the HR-based model (Model D) is significantly higher than Model A, and we observe a significant improvement in the type I error rate. In practice, a model that better discerns bankrupt firms is useful because of the asymmetry of misclassification costs. That is, the cost of misclassifying bankrupt firms as healthy is more severe because it implies a direct loss for creditors.

Comparing the results of Tables 4 and 6, the relevance of the inclusion of HR variables into models is different depending on the nature of the criterion used to discriminate between failed and nonfailed firms. Comparing Models A and D in Tables 4 and 6, the HR variables significantly improve the prediction accuracy when financial distress is defined as the occurrence of two consecutive years with negative profit than when the criterion used to discriminate between failed and nonfailed firms is bankruptcy. This observation is true whether global (five cases in Table 4 vs. three cases in Table 6), type I errors (five cases in Table 4 vs. four cases in Table 6), or type II errors (two cases in Table 4 vs. zero cases in Table 6) are considered.

Therefore, HR variables are more relevant when firms are in an upstream stage of the failure process. These variables are likely to face adjustments in the initial steps of the failure process to address profitability issues and act as a buffer to protect the firm from bankruptcy; moreover, because HR is generally a significant source of costs for firms, adjustments are likely in declining firms. When firms face a downstream stage of the corporate failure process such as bankruptcy, which is considered a more severe form of failure, issues other than profitability arise (e.g., liquidity and solvency), implying various adjustment processes, and the impact of HR variables is less pronounced.

5 | CONCLUSION

We analyze the potential of incorporating HR variables into corporate failure prediction models. Two reasons prompted us to conduct this study aiming to build a business failure prediction model using HR variables. First, the inclusion, into business failure prediction models, of pertinent nonfinancial variables generally translates into a more accurate prediction. Second, although HRM is a very important concern for all types of businesses and its impact on performance is widely debated in the academic literature, no business failure prediction model includes HR variables (different than the ones linked to top management teams) so far.

The results show that this unused data source should be included in corporate failure models because HR variables add complementary predictive power. Besides, our variable selection procedure allowed us to isolate the most discriminant HR variables: the number of training hours/average number of workers and the proportion of permanent working contracts. These variables cover two dimensions of Huselid's (1995) HRM practices classification: employee recruitment and selection procedures and employee training. Our results are in line with the report of Ng and Siu (2004), Ballot, Fakhfakh, and Taymaz (2006), and Aubert, Crépon, and Zamora (2009) that the investment in training is profitable for companies and argue with Bester, Milliou, and Petrakis (2012), Huselid (1995) and Pfeffer and Veiga (1999) that higher wages lead to higher workers productivity.

Our evidence indicates that a model based on HR variables better predicts failed firms. Specifically, HR variables are significantly relevant when failed firms have experienced a profound financial distress situation. Thus, this model is crucial for financial institutions (e.g., to estimate the risk of loans and ensure a firm will be able to reimburse it). A primary implication for entities interested in predicting firm failure (e.g., banks, rating agencies) is that their models should include information about HR characteristics, which emerge as explanatory components of bankruptcy. In this regard, HR characteristics may be easily collected for Belgian datasets because Belgian firms (of more than 20 employees) are required to publish a social statement Taking into account this fact, the collection cost (in terms of time) is negligible. Besides, they play a significant role as explanatory variables to enhance the forecasting performance of corporate failure models. In particular, it allows to better discern failed firms, which may be a rather useful model because of the asymmetry of misclassification costs. Thus, trade-off between efficiency and time consumption is positive, although this model may be limited to countries in which this information is available.

Additionally, HR variables do not have the same predictive power when incorporated into prediction models at different phases of corporate failure, from financial distress to bankruptcy. The results indicate better prediction accuracy during the initial symptoms of corporate failure (i.e., financial distress), which might be the focus of further research.

As only an historical of 2 years was available for most firms in our database, we were limited into our analyses. Although du Jardin (2015) argued that warning signs are mostly seen 3 years before failure, as per Altman et al. (2016), some nonfinancial variables can be significant predictors of bankruptcies for as long as 10 years. Therefore, we suggest analyzing the changes in HRM on a period of more than 2 years, taking into account that different firms typify unique patterns of decline. Moreover, although the importance of top-management teams variables into business failure prediction models has been proved, these kind of data were unavailable from Bel-First database. Nevertheless, a model combining top-management teams variables with financial variables and HR variables might be the focus of further research. Finally, future research might incorporate new indicators instead of being confined to already known corporate failure models.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Bureau Van Dijk (https://belfirst.bvdinfo.com/). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Bureau Van Dijk.

ENDNOTES

[1] The unbalanced ratios in samples (i.e., non-failed firms outnumber failed firms) is an intrinsic characteristic in bankruptcy studies that is detrimental to model performance and raises other concerns (Veganzones & Séverin, 2018). Thus, a widespread solution is to apply a matching procedure to pair the samples (Ciampi, 2015; Manzaneque, García-Pérez-De-Lema, & Antón Renart, 2015). We followed this procedure and chose a non-failed firm for each failed firm by randomly pairing those of similar size (i.e., measured by total assets and turnover) and belonging to the same industry sector.

[2] The results of the variable selection methods used to select financial ratios and HR variables included in the corporate failure models are available in Appendix A.

[3] The threshold model was implemented in STATA 15, in which we found the number of thresholds using the Akaike information criterion.

[4] Threshold value = 2.55.

REFERENCES

Addessi, W. (2014). The productivity effect of permanent and temporary labor contracts in the Italian manufacturing sector. *Economic Modelling*, *36*, 666–672. https://doi.org/10.1016/j.econmod.2013.09.054

Altman, E., Iwanicz-Drozdowska, M., Laitinen, E., & Suvas, A. (2016). Financial and nonfinancial variables as long-horizon predictors of bankruptcy. *The Journal of Credit Risk*, *12*, 49–78. https://doi.org/10.21314/JCR.2016.216

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*, 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Altman, E. I. (2000). Predicting financial distress of companies: Revisiting the *Z*-score and ZETA models. Working paper, Stern School of Business, New York University.

Altman, E. I., Sabato, G., & Wilson, N. (2010). The value of non-financial information in small and medium-sized enterprise risk management. *The Journal of Credit Risk*, *6*, 1–33.

Argenti, J. (1976). Corporate planning and corporate collapse. *Long Range Planning*, *9*, 12–17. https://doi.org/10.1016/0024-6301(76)90006-6

Arppe, A., Back, B., Eklund, T., Magnusson, C., Vanharanta, H., & Visa, A. (2005). The language of quarterly reports as an indicator of change in the company's financial status. *Information & Management*, *42*, 561–574.

Aubert, P., Crépon, B., & Zamora, P. (2009). Le rendement apparent de la formation continue dans les entreprises: effets sur la productivité et les salaires. *Économie & prévision*, *187*, 25–46. https://doi.org/10.3406/ecop.2009.7874

Balcaen, S., Manigart, S., & Ooghe, H. (2011). From distress to exit: Determinants of the time to exit. *Journal of Evolutionary Economics*, *21*, 407–446. https://doi.org/10.1007/s00191-010-0192-2

Balcaen, S., & Ooghe, H. (2004). Alternative methodologies in studies on business failure: Do they produce better results than the classical statistical methods. *Vlerick Leuven Gent Management School Working Paper Series*, *16*, 1–44.

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: An overview of the classic statistical methodologies and their related problems. *The British Accounting Review*, *38*, 63–93. https://doi.org/10.1016/j.bar.2005.09.001

Ballot, G., Fakhfakh, F., & Taymaz, E. (2006). Who benefits from training and R&D, the firm or the workers? *British Journal of Industrial Relations*, *44*, 473–495. https://doi.org/10.1111/j.1467-8543.2006.00509.x

Barney, J. B., Ketchen, D. J., & Wright, M. (2011). The future of resource-based theory: Revitalization or decline? *Journal of Management*, *37*, 1299–1315. https://doi.org/10.1177/0149206310391805

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

Becchetti, L., & Sierra, J. (2003). Bankruptcy risk and productive efficiency in manufacturing firms. *Journal of Banking & Finance*, *27*, 2099–2120. https://doi.org/10.1016/S0378-4266(02)00319-9

Becker, B. E., Huselid, M. A., Pickus, P. S., & Spratt, M. F. (1997). HR as a source of shareholder value: Research and recommendations. *Human Resource Management*, *36*, 39–47. https://doi.org/10.1002/(SICI)1099-050X(199721)36:1<39::AID-HRM8>3.0.CO;2-X

Bendickson, J. S., & Chandler, T. D. (2019). Operational performance: The mediator between human capital developmental programs and financial performance. *Journal of Business Research*, *94*, 162–171. https://doi.org/10.1016/j.jbusres.2017.10.049

Bester, H., Milliou, C., & Petrakis, E. (2012). Wage bargaining, productivity growth and long-run industry structure. *Labour Economics*, *19*, 923–930. https://doi.org/10.1016/j.labeco.2012.09.006

Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers. In *Proceedings of the fifth annual workshop on computational learning theory* (pp. 144–152). New York: Association for Computing Machinery.

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees*. London: Taylor & Francis.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *Journal of Finance*, *63*, 2899–2939. https://doi.org/10.1111/j.1540-6261.2008.01416.x

Chaganti, R. S., Mahajan, V., & Sharma, S. (1985). Corporate board size, composition and corporate failures in retailing industry. *Journal of Management Studies*, *22*, 400–417. https://doi.org/10.1111/j.1467-6486.1985.tb00005.x

Ciampi, F. (2015). Corporate governance characteristics and default prediction modeling for small enterprises. An empirical analysis of Italian firms. *Journal of Business Research*, *68*, 1012–1025. https://doi.org/10.1016/j.jbusres.2014.10.003

Ciampi, F., Cillo, V., & Fiano, F. (2018). Combining Kohonen maps and prior payment behavior for small enterprise default prediction. *Small Business Economics*, *54*, 1007–1039. https://doi.org/10.1007/s11187-018-0117-2

Combs, J., Liu, Y., Hall, A., & Ketchen, D. (2006). How much do high-performance work practices matter? A meta-analysis of their effects on organizational performance. *Personnel Psychology*, *59*, 501–528. https://doi.org/10.1111/j.1744-6570.2006.00045.x

Crook, T. R., Ketchen, D. J., Combs, J. G., & Todd, S. Y. (2008). Strategic resources and performance: A meta-analysis. *Strategic Management Journal*, *29*, 1141–1154. https://doi.org/10.1002/smj.703

Daily, C., & Dalton, D. (1994). Corporate governance and the bankrupt firm: An empirical assessment. *Strategic Management Journal*, *15*, 643–654. https://doi.org/10.1002/smj.4250150806

Donoher, W. J. (2004). To file or not to file? Systemic incentives, corporate control, and the bankruptcy decision. *Journal of Management*, *30*, 239–262. https://doi.org/10.1016/j.jm.2003.02.003

du Jardin, P. (2012). The influence of variable selection methods on the accuracy of bankruptcy prediction models. *Bankers, Markets & Investors*, *116*, 20–39.

du Jardin, P. (2015). Bankruptcy prediction using terminal failure processes. *European Journal of Operational Research*, *242*, 286–303. https://doi.org/10.1016/j.ejor.2014.09.059

Dyer, L., & Reeves, T. (1995). Human resource strategies and firm performance: What do we know and where do we need to go? *International Journal of Human Resource Management*, *6*, 656–670. https://doi.org/10.1080/09585199500000041

Farooq, U., & Qamar, M. A. J. (2019). Predicting multistage financial distress: Reflections on sampling, feature and model selection criteria. *Journal of Forecasting*, *38*, 632–648. https://doi.org/10.1002/for.2588

Gong, Y., Law, K. S., Chang, S., & Xin, K. R. (2009). Human resources management and firm performance: The differential role of managerial affective and continuance commitment. *Journal of Applied Psychology*, *94*, 263–275. https://doi.org/10.1037/a0013116

Gordini, N. (2014). A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy. *Expert Systems with Applications*, *41*, 6433–6445. https://doi.org/10.1016/j.eswa.2014.04.026

Hambrick, D. C., & D'Aveni, R. A. (1988). Large corporate failures as downward spirals. *Administrative Science Quarterly*, *33*, 1. https://doi.org/10.2307/2392853

Hambrick, D. C., & D'Aveni, R. A. (1992). Top team deterioration as part of the downward spiral of large corporate bankruptcies. *Management Science*, *38*, 1445–1466. https://doi.org/10.1287/mnsc.38.10.1445

Hansen, B. E. (2000). Sample splitting and threshold estimation. *Econometrica*, *68*, 575–603. https://doi.org/10.1111/1468-0262.00124

Harel, G. H., & Tzafrir, S. S. (1999). The effect of human resource management practices on the perceptions of organizational and market performance of the firm. *Human Resource Management*, *38*, 185–199. https://doi.org/10.1002/(SICI)1099-050X(199923)38:3<185::AID-HRM2>3.0.CO;2-Y

Heo, J., & Yang, J. Y. (2014). AdaBoost based bankruptcy forecasting of Korean construction companies. *Applied Soft Computing*, *24*, 494–499. https://doi.org/10.1016/j.asoc.2014.08.009

Huang, G. B., Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, *70*, 489–501. https://doi.org/10.1016/j.neucom.2005.12.126

Huselid, M. A. (1995). The impact of human resource management practices on turnover, productivity, and corporate financial performance. *Academy of Management Journal*, *38*, 635–672.

Kainulainen, L., Miche, Y., Eirola, E., Yu, Q., Frénay, B., Séverin, E., & Lendasse, A. (2014). Ensembles of local linear models for bankruptcy analysis and prediction. *Case Studies in Business, Industry and Government Statistics*, *4*, 116–133.

Keasey, K., & Watson, R. (1987). Non-financial symptoms and the prediction of small company failure: A test of Argenti's hypotheses. *Journal of Business Finance & Accounting*, *14*, 335–354. https://doi.org/10.1111/j.1468-5957.1987.tb00099.x

Kim, M.-J., & Kang, D.-K. (2010). Ensemble with neural networks for bankruptcy prediction. *Expert Systems with Applications*, *37*, 3373–3379. https://doi.org/10.1016/j.eswa.2009.10.012

Kim, M.-J., Kang, D.-K., & Kim, H. B. (2015). Geometric mean based boosting algorithm with over-sampling to resolve data imbalance problem for bankruptcy prediction. *Expert Systems with Applications*, *42*, 1074–1082. https://doi.org/10.1016/j.eswa.2014.08.025

Laitinen, E. K. (1999). Predicting a corporate credit analyst's risk estimate by logistic and linear models. *International Review of Financial Analysis*, *8*, 97–121. https://doi.org/10.1016/S1057-5219(99)00012-5

Laitinen, E. K. (2008). Data system for assessing probability of failure in SME reorganization. *Industrial Management & Data Systems*, *108*, 849–866. https://doi.org/10.1108/02635570810897964

Lajili, K., & Zéghal, D. (2010). Corporate governance and bankruptcy filing decisions. *Journal of General Management*, *35*, 3–26. https://doi.org/10.1177/030630701003500401

Lohmann, C., & Ohliger, T. (2019). Using accounting based information on young firms to predict bankruptcy. *Journal of Forecasting*, *38*, 803–819. https://doi.org/10.1002/for.2586

Manzaneque, M., García-Pérez-De-Lema, D., & Antón Renart, M. (2015). Bootstrap replacement to validate the influence of the economic cycle on the structure and the accuracy level of business failure prediction models: Economic cycle and business failure prediction models. *Journal of Forecasting*, *34*, 275–289. https://doi.org/10.1002/for.2327

Messier, W. F. Jr., & Hansen, J. V. (1988). Inducing rules for expert system development: An example using default and bankruptcy data. *Management Science*, *34*, 1403–1415. https://doi.org/10.1287/mnsc.34.12.1403

Micha, B. (1984). Analysis of business failures in France. *Journal of Banking & Finance*, *8*, 281–291. https://doi.org/10.1016/0378-4266(84)90008-6

Ng, Y. C., & Siu, N. Y. M. (2004). Training and enterprise performance in transition: Evidence from China. *The International Journal of Human Resource Management*, *15*, 878–894. https://doi.org/10.1080/0958519042000192997

Oh, I. S., Kim, S., & Van Iddekinge, C. H. (2015). Taking it to another level: Do personality-based human capital resources matter to firm performance? *Journal of Applied Psychology*, *100*, 935–947. https://doi.org/10.1037/a0039052

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*, 109–131. https://doi.org/10.2307/2490395

Pervan, I., & Kuvek, T. (2013). The relative importance of financial ratios and nonfinancial variables in predicting of insolvency. *Croatian Operational Research Review*, *4*, 187–197.

Pfeffer, J., & Veiga, J. F. (1999). Putting people first for organizational success. *The Academy of Management Executive*, *13*, 37–48.

Platt, H., & Platt, M. (2012). Corporate board attributes and bankruptcy. *Journal of Business Research*, *65*, 1139–1143. https://doi.org/10.1016/j.jbusres.2011.08.003

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. New York: Free Press.

Rao, C. R., & Mitra, S. K. (1971). Further contributions to the theory of generalized inverse of matrices and its applications. *Sankhyā: The Indian Journal of Statistics, Series a*, *33*, 289–300.

Rauch, A., & Rijsdijk, S. A. (2013). The effects of general and specific human capital on long-term growth and failure of newly founded businesses. *Entrepreneurship Theory and Practice*, *37*, 923–941. https://doi.org/10.1111/j.1540-6520.2011.00487.x

Santana, M., Valle, R., & Galan, J.-L. (2017). Turnaround strategies for companies in crisis: Watch out the causes of decline before firing people. *Business Research Quarterly*, *20*, 206–211.

Shin, K. S., Lee, T. S., & Kim, H. J. (2005). An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications*, *28*, 127–135. https://doi.org/10.1016/j.eswa.2004.08.009

Shin, K.-S., & Lee, Y.-J. (2002). A genetic algorithm application in bankruptcy prediction modeling. *Expert Systems with Applications*, *23*, 321–328. https://doi.org/10.1016/S0957-4174(02)00051-9

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

Sun, J., Li, H., Huang, Q.-H., & He, K.-Y. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems*, *57*, 41–56. https://doi.org/10.1016/j.knosys.2013.12.006

Tang, X., Li, S., Tan, M., & Shi, W. (2020). Incorporating textual and management factors into financial distress prediction: A comparative study of machine learning methods. *Journal of Forecasting*, *39*, 769–787. https://doi.org/10.1002/for.2661

Theriou, G. N., & Chatzoglou, P. D. (2008). Enhancing performance through best HRM practices, organizational learning and knowledge management: A conceptual framework. *European Business Review*, *20*, 185–207. https://doi.org/10.1108/09555340810871400

Tian, S., Yu, Y., & Guo, H. (2015). Variable selection and corporate bankruptcy forecasts. *Journal of Banking & Finance*, *52*, 89–100. https://doi.org/10.1016/j.jbankfin.2014.12.003

Tobback, E., Bellotti, T., Moeyersoms, J., Stankova, M., & Martens, D. (2017). Bankruptcy prediction for SMEs using relational data. *Decision Support Systems*, *102*, 69–81. https://doi.org/10.1016/j.dss.2017.07.004

Vapnik, V. (1998). The support vector method of function estimation. In J. A. K. Suykens & J. Vandewalle (Eds.), *Nonlinear modeling* (pp. 55–85). Boston: Springer. https://doi.org/10.1007/978-1-4615-5703-6_3

Veganzones, D., & Séverin, E. (2018). An investigation of bankruptcy prediction in imbalanced datasets. *Decision Support Systems*, *112*, 111–124. https://doi.org/10.1016/j.dss.2018.06.011

Yang, Z. R., Platt, M. B., & Platt, H. D. (1999). Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research*, *44*, 67–74. https://doi.org/10.1016/S0148-2963(97)00242-7

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, *22*, 59–82. https://doi.org/10.2307/2490859

AUTHOR BIOGRAPHIES

Xavier Brédart is an associate professor in mathematics' department at Warocqué Business School of the University of Mons (Belgium). He is also a member of the research institute in human sciences humanOrg. He teaches mathematics and accounting courses. His research interests are business failure (prediction, analysis, and recommendations) and corporate governance (analysis and effectiveness of corporate governance mechanisms and governance laws and codes). In 2015, he created the International Corporate Bankruptcy Conference..

Eric Séverin is a professor of finance at the University of Lille, and he is a specialist in corporate finance. His research interests are the following: bankruptcy and financial structure, information quality and financial applications of machine learning in the field of bankruptcy predictions.

David Veganzones is an assistant professor in finance department at ESCE International Business School of Paris (France). He holds a doctorate in management and finance from the Institute d'Administration des Entreprises (IAE), University of Lille, France. He is interested in various domains of bankruptcy prediction and the application of machine learning to corporate finance. He is a member of the research institute INSEEC U Research Center.

How to cite this article: Brédart X, Séverin E, Veganzones D. Human resources and corporate failure prediction modeling: Evidence from Belgium. *Journal of Forecasting*. 2021;1–17. https://doi.org/10.1002/for.2770

APPENDIX A.

RESULTS OF THE VARIABLE SELECTION METHODS

TABLE A1 Variables selected by stepwise search with Wilks's lambda as stopping criterion

Financial ratios	**Selection frequency**
Quick assets/current liabilities	92.5%
EBIT/value added	89.5%
Total sales/total assets	79%
Current assets/current liabilities	77%
Long term debt/total assets	72.5%
Inventory/total sales	70%
Human resource variables	**Selection frequency**
Proportion of permanent working contracts year t	78%
Downsizing variation between year t and $t-1$	73%
(Number training hours/average number of workers) year t	71%

TABLE A2 Variables selected by stepwise search with χ^2 as stopping criterion

Financial ratios	**Selection frequency**
Financial debt/cash flow	89.5%
Quick assets/current liabilities	87%
Value added/total sales	79.5%
EBITDA/total sales	75.5%
EBITDA/permanent equity	75%
Long term debt/total assets	74.5%
Inventory/total assets	71.5%
Human resource variables	**Selection frequency**
Downsizing variation between year t and $t-1$	79.5%
Proportion of permanent working contracts year t	75.5%
(Number training hours/average number of workers) year t	72%

TABLE A3 Variables selected by geometric algorithm

Financial ratios	**Selection frequency**
Profit before tax/shareholder funds	85.5%
EBITDA/permanent equity	83%
EBIT/value added	79.5%
Financial debt/cash flow	75%
Total sales/total assets	75.5%
Quick assets/current liabilities	71%
Human resource variables	**Selection frequency**
Proportion of permanent working contracts year t	80%

TABLE A4 Variables selected by partial swarm optimization

Financial ratios	Selection frequency
EBIT/value added	94%
EBITDA/permanent equity	89%
Long term debt/total assets	82%
Financial debt/cash flow	81%
Total sales/total assets	73.5%
Profit before tax/shareholder funds	71.5%
Human resource variables	**Selection frequency**
Proportion of permanent working contracts year t	80.5%
Variation of cost of labor between year t and $t-1$	76.5%
(Number training hours/average number of workers) year t	75.5%

APPENDIX B.

REVISED z SCORE (Altman, 2000)

z score estimation based on the following formula:

$$z = 0.717 * X1 + 0.847 * X2 + 3.107 * X3 + 0.42 * X4 + 0.998 * X5,$$

where

X1 = current assets less the current liabilities divided by the total assets,

X2 = retained earnings divided by the total assets,

X3 = earnings before interest and taxes divided by the total assets,

X4 = book value of equity divided by the total liabilities, and

X5 = sales divided by the total assets.