Journal of Finance & Economics
Volume 1, Issue 3 (2013), 01-26
ISSN 2291-4951 E-ISSN 2291-496X
Published by Science and Education Centre of North America

International Applicability of Corporate Failure Risk Models Based on Financial Statement Information: Comparisons across European Countries

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Abstract: The objective of the study is, firstly, to analyse the predictability of financial distress in different European countries. Secondly, the objective is to compare predictability across countries. Thirdly, the objective is to investigate possibilities to develop a generic uniform model to predict distress in each country over Europe. The sample includes over one million active and tens of thousands financially distressed firms from 30 European countries. For each country, a prediction model of its own is estimated. The models and their performance in prediction accuracy are compared across countries. Finally, a uniform generic model is estimated for the sample including all countries and its prediction accuracy is assessed by country. The results show that there are differences in the form and strength of prediction models across different European countries. However, it is possible to develop a uniform generic model resulting in a reasonably high rate of classification accuracy for most countries.

JEL Classifications: G15, G32, G33

Keywords: financial distress, bankruptcy, credit risk, failure prediction, international comparison, European countries

1. Introduction

Financial distress or failure can be defined as the inability of a business firm to pay its financial obligations as they mature (Beaver, 1966, p.80). Failure will cause large economic and social losses for each stakeholder of the firm. At the level of national economy, business failures refer to inefficient allocation of domestic capital and may lead to severe domestic or even international crises. In international context, failures form a serious risk factor for international investors and exacerbate efficient allocation of financial capital between countries. Because of its importance, financial distress prediction has played an important role in financial research over many decades (see Jones & Hensher, 2004; Charitou, Neophytou, & Charalambous, 2004; Altman & Hotchkiss, 2006; Balcaen & Ooghe, 2006; Lensberg, Eilifsen, & McKee, 2006). Prediction models are applied by managers of distressed firms, bankers, lending specialists, accounts receivable managers, investors, security analysts, auditors, bankruptcy & reorganization lawyers, and judges (Altman & Hotchkiss, 2006, p.281-296). These models are important in warning for impeding financial distress and giving time for the stakeholders to timely react to the crisis. They help managers to avoid a failure but also the external stakeholders such as investors to assess the risk associated with the firm.

Since the economic cost of business failures is significant, countries all over the world are concerned with avoiding financial crises of business firms. In this avoidance, efficient country-specific distress prediction models can play an important role. Therefore, prediction models have been developed in many countries to provide stakeholders with tools to assess failure risk. Altman and Narayanan (1997) and Altman and Hotchkiss (2006, p.259-264) present a review of country-specific distress prediction models developed in 22 countries while Bellovary, Giacomino, and Akers (2007) refer to models for 18 countries. Altman and Narayanan (1997, p.1-2) state that while the economic forces shaping the outcomes in various countries may diverge, the researchers share a striking similarity in their approach to distress prediction. Nearly every study contrasts the profile of failed firms with that of non-failed firms to draw conclusions about the coincident factors of failure. However, the variables and their weights (model structures) considerably differ between country-specific models making the application of a model to foreign firms questionable. Therefore, the models are difficult to compare and they are mostly useless in comparisons across countries. However, investors and other stakeholders have a growing need to analyze the financial risk of foreign firms and to make international comparisons (Choi, Frost, & Meek, 1999).

The need for international comparisons is originated in the tremendous growth in international capital issuance and trading in recent years due to a surge of privatizations, economic integration in Europe, relaxation of capital controls, and many other causes (Choi *et al.*, 1999, p.289; Whittington, 2005). Furthermore, in Western Europe alone, the number of seriously distressed firms (insolvencies) during the last years has been about 180.000 which has enormous economic consequences for EU (Creditreform, Insolvencies in Europe 2010/11).

The purpose of this study is to make a contribution to international distress prediction research by responding to the call for international comparisons and uniform models in financial distress prediction. It is worth stressing that a major benefit of a well performing international model would be that its users could carry out their international analyses within the realm of one single model. Different models, their structures, and their outputs are difficult (if not frustrating) to compare - impairing the decision making process.

Our study is based on three objectives. First, the objective is to analyze the predictability of financial distress in different European countries. Secondly, the objective is to compare predictability across countries. Thirdly, the objective is to investigate possibilities to develop a generic uniform model to predict distress in most countries over Europe.

The data of the study includes over one million active and tens of thousands failed firms from 30 European countries. For each country, a country-specific prediction model of its own will be estimated. The models and their performance in prediction accuracy are compared across countries. Finally, a uniform generic model is estimated for the sample including all countries and its prediction accuracy is assessed by country. The models are estimated by the logistic regression analysis using familiar financial ratios based on the bankruptcy theory (profitability, liquidity, solidity, size, volatility) as predictors. This study is limited to modeling of bankruptcy risk based on financial statement information only to show the value of this information in international context of bankruptcy prediction. Non-financial variables and control variables measuring country influences or industry effects are intentionally excluded.[1] We believe that such variables could improve measurement accuracy, but at this pioneering stage it is most instructive to focus on the predictive value brought about by financial statement information in developing an international uniform failure prediction model.

The structure of the paper is as follows. First, the background and objectives of the study were discussed in the introductory section. Prior studies and two general research hypotheses based on these studies are briefly discussed in the second section while the third section presents the data and methods of the study. The empirical results are discussed in the fourth section. In this context, country-specific models and the uniform model are presented and discussed. In addition, the reasons for low country-specific performance and low uniformity are statistically assessed by the regression analysis and the countries are classified to homogenous groups. Finally, the last section presents a summary of the results, discusses the limitations of the study and outlines potential trends for future research.

2. Prior Studies and Research Hypotheses

2.1 Country-Specific Models

Financial distress prediction has played an important role in financial research over many decades (Jones & Hensher, 2004; Altman & Hotchkiss, 2006; Balcaen & Ooghe, 2006; Lensberg *et al*., 2006). This research has produced important country-specific prediction models to identify early warnings of impending financial distress (Altman & Narayanan, 1997). However, distress research is fragmented and mainly empirical. Therefore, it is obvious that distress research suffers from lack of theoretical analysis which weakens the understanding and conceptualization of the event of interest (failure or distress), the choice of predictors, and the justification of the functional form between predictors (Dimitras, Zanakis, & Zopounidis, 1996; Balcaen & Ooghe, 2006; Lensberg *et al*., 2006). It is obvious that all these weaknesses impair the generalization of estimated failure prediction models. These kinds of empirical models are strongly associated with the original estimation data and cannot be efficiently generalized for different kinds of contexts such as for different countries in international analysis. Therefore, their usefulness is strictly limited in international comparisons and decision-making of international investors. Thus, there is an urgent call for studies estimating theory-based prediction models from data of different countries, investigating possibilities to generalize the models from the country of origin to other countries, and to develop a uniform model generalizable for several countries.

Failure research includes a couple of wide international comparisons of distress prediction models. Altman & Narayanan (1997; see also Altman & Hotchkiss, 2006, p.259-264) present a survey of models estimated in 22 different countries and comment on their similarities and differences. The authors found a striking similarity in their approach to distress prediction (in contrasting the profile of failed and non-failed firms) but significant differences in definition of failure concept, modeling techniques used (reflecting differences in the functional form of models), financial variables included, and in data issues. In these studies, failure could for example mean bankruptcy, bond default, bank loan default, delisting of a firm, government intervention, and liquidation. The modeling techniques included discriminant analysis, logit analysis, probit analysis, recursive partitioning, Bayesian analysis, survival analysis, and neural networks. Practically, every model was based on different financial variables. In many country-specific models, the estimation data were very limited and any test data were not used. Because of all these differences, the proper comparison of the country-specific models is not possible and their generalizability for other countries cannot be assessed.

Bellovary *et al*. (2007) present a review of bankruptcy prediction studies and refer to country-specific models in 18 different countries. In the same way as above, the authors address the diverse definition of failure, data used, modeling techniques and variables included. In addition, they refer to differences in validation methods and prediction timeframes applied. To show the diversity in selecting financial variables for the models, the authors calculate that the number of variables in the models ranged from 1 to 57 and 752 different variables were used in prediction models so that 674 variables were utilized in only one or two of the studies. The studies used discriminant analysis (63), logit analysis (36), probit analysis (7), neural networks (40), or some other (26) modeling technique. Many of the studies were concentrated on large manufacturing or retailing firms ignoring smaller firms and other industries. In overall, 77 studies tested the prediction results in a hold-out sample while 87 studies did not. The classification accuracy of the models varied significantly from 20% to 100%. This review clearly shows that failure research is strongly fragmented, the proper comparison of the models is impossible, and that it is not possible to assess the international generalizability of country-specific models.

2.2 Country-Specific Models Tested in another Country

Ooghe and Balcaen (2007) examined the performance of seven different prediction models on Belgian failure data to test whether country-specific models can be transferred and applied to a new data setting. The authors state that this kind of analysis is important because many international financial information agencies apply failure prediction models on a totally different dataset of firms than the ones they are designed for. The authors found that after re-estimation of the coefficients, some of the examined models were widely usable in Belgium. The estimation technique, complexity and the number of variables did not explain predictive performance. The study shows that it is possible to generalize prediction models across countries at least when the models are re-estimated and variables are carefully chosen in a theoretically-justified way.

2.3 Country-Specific and International Uniform Models Tested across Countries

Laitinen (2002) has used a different setting to assess international comparability in financial rating of technology firms. He used financial data from the US and 17 European countries to investigate possibilities to develop a uniform rating form. The author measured the three-year financial success of firms and used financial statements before the event period to predict this success. He measured financial success by a factor of several variables and classified firms into two crude classes with respect to success (lower/upper success). Then, Laitinen applied binary logistic regression analysis to estimate country-specific prediction models and a uniform model based on data from all countries. He showed that the uniform model generally performed well showing that it is possible to develop an overall rating model. The highest classification accuracy was got in Germany, Belgium, Italy, Finland, and Greece while the poorest one was found in Switzerland, Ireland, and Portugal. Laitinen measured the uniformity of rating rules by the difference between the classification accuracy of the uniform model applied to the country data and that of the country-specific model. The highest uniformity was shown by Sweden, France, Germany, Spain and Finland whereas the poorest was found for Luxembourg, Belgium, Portugal and Austria. Finally, Laitinen classified the countries into following four classes on the basis of the similarity of country-specific model predictions: Spain-France, Greece-Portugal, Ireland-US, and Luxembourg classes. In summary, the study shows that it is possible to develop a reliable uniform prediction model to assess firms in different countries. However, the accuracy of this kind of model may show significant differences between countries. In addition, country-specific models may behave in a very different way with respect to predictability. As these models did not attempt to predict bankruptcy, loan default or any other form of financial distress, these results, although promising, cannot be generalized to failure prediction modeling.

2.4 Factors Affecting International Applicability of Failure Risk Models

It is obvious that the international generalizability of failure prediction models based on financial statement variables is affected by country-specific differences in many factors. Event definition, economic environment, legislation, and culture affect directly the characteristics of the target event (failure) (see Ward & Foster, 1997; Beraho & Elisu, 2010), while differences in accounting practices jeopardize the ability of the financial predictors to reflect these characteristics in an identical way. It is said that differences in accounting practices can alone destroy international comparability between firms (Choi & Levich, 1991). The literature offers a large number of possible reasons for international differences (see Belkaoui, 1985; Choi & Mueller, 1992; Radebaugh & Gray, 1993; Nobes & Parker, 1998; Nobes, 1998). In Europe, there are differences in accounting practices in spite of the harmonization efforts (Herrmann & Thomas, 1995; Batt, 1998, Schipper, 2005; Whittington, 2005; Burlaud & Colasse, 2011). These differences have led several researchers to develop international classifications of accounting practices to demonstrate the incomparability between countries (Nobes & Parker, 1998). Mueller (1967) classified the accounting systems indirectly on the basis of differences in the importance of economic, governmental and business factors. Buckley and Buckley (1974), AAA (1977) and Nair and Frank (1980) presented classifications based on empirical data. Nobes (1983) identified several problems with the previous classifications (lack of precision, lack of a model, lack of hierarchy, and lack of judgment) and presented himself a hierarchic classification of fourteen countries. Doupnik and Salter (1993) tested the Nobes (1983) classification using the cluster analysis and found nine separate clusters. The international diversity of accounting practices obviously implies that even if country-specific prediction models are based on the same technique and include the same financial variables, they may refer to different accounting events and behave in a different way due to different content of financial variables.

2.5 Purpose of the Study and the Research Hypotheses

The purpose of this study is to test the predictability of failure in several European countries by estimating country-specific models for these countries using the same modeling technique and the same theory-based financial variables. In addition, the purpose is to use the same technique and the same financial variables to estimate a uniform prediction model based on data from every country. Prior research shows that current country-specific models are very different with respect to functional form and variables included. Therefore, it is impossible to compare these models in a proper manner with respect to international generalization. However, when re-estimated, some of the models can be transferred to other countries. If the same technique and the same variables are used to estimate country-specific models, the models in some countries perform well whereas in some other countries they do not perform properly. In spite of the differences between countries, it may be possible to develop a uniform prediction model showing a moderate performance in most countries. It may not be possible to develop a uniform model that performs well in each country due to the differences in culture, economic environment, legislation, and especially accounting practices. In some cases, accounting practices may alone destroy international comparability between countries. This review of previous research leads us to draw the following general research hypotheses:

Hypothesis 1 (H1): *The country-specific prediction models differ significantly from each other although being estimated using the same modeling technique and the same financial variables.*

Hypothesis 2 (H2): *It is possible to estimate a uniform prediction model performing well in most countries.*

3. Data and Methodology

3.1 Empirical Data

The empirical data of this study are extracted from the ORBIS database of Bureau Van Dijk (BvD). ORBIS is a commercial database which contains administrative information on over 50 million European companies, of which income statement and balance sheet information was available for about 8 million companies. More than 99% of the companies covered in this database are private companies. The information for the ORBIS Europe is sourced from almost 30 different information providers using a multitude of data sources, typically national and/or local public institutions collecting data to fulfill legal and/or administrative requirements. The ORBIS database organizes these public data from administrative sources and filters them into various standard formats to facilitate searching and company comparisons. The ORBIS formats have been derived from the most common formats used for the presentation of business accounts in Europe, following

European Union guidelines (Ribeiro, Menghinello, & Backer, 2010). It is clear that international comparability may be a problem when administrative firm-level data are internationally pooled. While in administrative data the definition of variables is usually less harmonized, this is less of a problem in the ORBIS database because of the common international format of balance sheets. For example, although some discrepancies in profit/loss statements may arise following differences in fiscal systems across countries, balance sheet variables largely adhere to international standards. Therefore, ORBIS provides us with a useful database for our study.

In setting the criteria for the selection of the observations, our major aim is to ensure that the data is highly encompassing, while at the same time avoiding firms whose financial statement structure or company form make them poorly comparable to the majority of sample. Therefore we require, firstly, that the firm must be an industrial company (banks and insurance companies are excluded). Secondly, its owners must have limited liability (whereby e.g. partnerships and sole proprietors are left out of the study). Since for very small firms the financial statement numbers are less relevant than other characteristics (such as the experience and wealth of the owners), very small firms are excluded (Balcaen & Ooghe, 2006). As a practical minimum size restriction, the Total Assets must have exceeded 100 thousand EUR at least once in the available time series for a firm. The time span of fiscal years potentially available for this study ranges from 2002 to 2010. Because the last financial statements for failed firms in the database typically are from a financial period within 2007 and 2010, earlier years are excluded, for comparability, also for non-failed firms.

ORBIS has five classes for active firms (active; default of payment; receivership; dormant; branch) and seven classes for inactive firms which do not carry out business activities anymore (bankruptcy; dissolved; dissolved (merger); dissolved (demerger); in liquidation; branch; no precision). From these classes, only *active* is selected to represent non-distressed firms. In selecting the failed firms, we try to avoid ambiguity as much as possible by considering (with exceptions described below) a firm failed if its status in Orbis is stated as *bankruptcy*. Other classes conceptually close to failure are especially *receivership* (active) and *in liquidation* (inactive). Unfortunately, firms under receivership may already be successfully reorganized and thus should rather be classified as non-failed than failed. Firms *in liquidation* may, depending on the country, contain firms that have ceased activities due to reasons other than failure (mergers, discontinuing the operations of a daughter company or of a foreign branch, etc.). Therefore, for most countries, we select only firms that are coded as bankrupt. Yet, there are many countries in the database that have no firms (or only a handful) coded as bankrupt. In these cases we examined the other plausible status categories to determine if bankrupt or failed firms are coded under a different status heading. In case no such category could be identified, that country was excluded from the study (for example Austria, Hungary, Switzerland). Likewise, if there was found only a very small number of failed observations, the country was dropped from the study (e.g. Luxembourg, Liechtenstein, Montenegro, typically small countries). This was necessary because meaningful country-specific models cannot be estimated with only a handful of observations in the failed firm category. Furthermore, in case there were only a small number of observations coded as bankrupt, but a considerable number of firms existed in the other conceptually close categories, firms from these categories were included as well, and the country was not dropped. Finally, if we could identify that all failed firms are placed under a heading different from "bankruptcy", we included that country in the study. All these special countries are:

Country	*Status categories*
Bulgaria	In liquidation, Bankruptcy
Denmark	Inactive (no precision)
Germany	Active (receivership)
Greece	Active (receivership), In liquidation, Bankruptcy

Ireland	In liquidation, Active (receivership)
Malta	In liquidation
Norway	In liquidation
Portugal	Active (receivership), Bankruptcy
Slovenia	In liquidation
Spain	Active (receivership), In liquidation, Bankruptcy
Ukraine	In liquidation, Bankruptcy
United Kingdom	In liquidation, Active (receivership)

Thus, there exists potential ambiguity in the failure definitions across countries that could not be avoided, and these imperfections should be considered in interpreting the results. It should also be noted that the contents of different classes differ within European countries due to different legislations although there are obvious similarities in insolvency acts (Philippe & Partners, & Deloitte & Touche, 2002). However, we are confident that, irrespective of the country, in each class that was selected to represent failed firms, the vast majority of firms suffered from financial distress.

3.2 Statistical Methods

In the present study, (binary) logistic regression analysis (LRA) will be applied to estimate the prediction model for financial distress. The LR model will be estimated for each country separately and for the entire sample as to estimate the uniform (overall) model for the European countries. For this estimation, the dependent variable $Y = 0$ when the firm is non-distressed (non-failed) and $Y = 1$ when it is distressed (failed). In general, LRA can be used to predict a dependent variable on the basis of continuous or categorical independent variables and also to determine the percent of variance in the dependent variable explained by the independent variables. This analysis does not require that independent variables are multivariate normal or that groups have equal covariance matrices that are basic assumptions in linear discriminant analysis (Hosmer & Lemeshow, 1989). LRA creates a score (logit) L for every firm. It is assumed that the independent variables be linearly related to L. This score is used to determine the conditional probability to become distressed as follows:

$$p(Y=1\,|\,X)=\frac{1}{1+e^{-L}}=\frac{1}{1+e^{-(b_0+b_1x_1..+b_nx_n)}}\,. \tag{1}$$

where b_i (i =0,…,n) are coefficients and n is the number of independent variables x_i (i=1,…, n).

The LR models are estimated by the maximum likelihood method in SAS. The strength of association is assessed by the standard tests for LRA such as the R^2 Square and the Nagelkerke adjusted R^2. In estimation, the number of non-distressed firms is extremely high in comparison with the distressed firms. However, it is logical to assume that distress and non-distress affect the conditional probability of distress with equal weights. Therefore, the observations are weighted in the way that distressed and non-distressed firms get equal weights in estimation but the number of observations is set equal to the original sample size. This leads to the situation where the cut-off probability for distress is 50%. Technically, this situation is desirable, since the LRA assumes that midranges of probability are more sensitive to changes of values in independent variables to minimize the gray area (area of ignorance). However, the weighting of observations remarkably affects the statistical tests. Therefore, the absolute values of the Wald test and the Hosmer & Lemeshow test are not relevant in this weighted estimation and are not reported here. The former test is a test for the significance of the model coefficients while the latter test is often applied to test the linearity of the logit.

The classification accuracy of the LR model in the sample is measured in the country and overall models by the frequencies of Type I and Type II classification errors. The classification results are validated in the hold-out validation data (30% of the data). In addition, the AUC (Area Under Curve) measure extracted from the ROC (Receiver Operating Characteristic curve) is used to assess the accuracy. ROC curve is a plot of true positive rate against false positive rate for all different possible cut-points. These profiles show the trade-offs between Type I and Type II errors and represent statistically the cumulative probability distribution of default events. AUC measures the accuracy of the estimated model in relation to the perfect model. With a perfect model AUC is 1, and with a random model 0.5.

In distress prediction studies, predictors or financial ratios for the models are mainly selected on empirical grounds. This leads to the situation where the selection is sample specific and the resulted model is also specific for that sample (Zavgren, 1983). Karels and Prakash (1987, p.578) present a table showing a diverse selection of ratios in previous studies that is apparent given the limited normative basis for selecting ratios. Typically, the predictors are chosen in two vague stages (Balcaen & Ooghe, 2006, p.79-81): 1) initial set; and 2) final set. For example, Altman (1968) had 22 potentially useful ratios compiled for evaluation (initial set). Five of these ratios were selected as performing best together in the prediction model (final set). When comparing models across countries, it is important to pay attention to the choice of variables to avoid sample specific results. Bankruptcy theory can be used to give recommendations how the predictors should be selected and modeled to be theoretically justified in bankruptcy prediction (Scott, 1981). Scott (1981) contributed to bankruptcy theory by showing that the probability of failure is an explicit function of the expected value and the standard deviation of the change in retained earnings (net income minus dividends), and the current market value of equity, all divided by total assets. Thus, this kind of approach suggests that the profitability together with its volatility and the equity ratio are important predictors of bankruptcy. Scott also expanded the basic model and showed theoretically that the size and the liquidity of the firm can also affect bankruptcy probability. Scott (1981, p.342) concluded that bankruptcy prediction is both empirically feasible and theoretically explainable. Following the recommendations given by Scott (1981), the following six financial variables are selected to all our distress models: 1) return on assets ratio (profitability); 2) quick assets to total assets ratio (liquidity); 3) equity ratio (solvency); 4) semi-deviation in the return on assets ratio in two last years (volatility); 5) total assets (size); and (6) squared total assets (size).[2] The variables are all (except for semi-deviation) calculated for the first year prior to bankruptcy. The amount of quick assets is defined as Current assets – Inventories – Current liabilities. The semi-deviation only focuses on a negative change in return on assets ratio. The size of the firm (in terms of total assets) is measured by a parabola of second order because the sign of the size effect can change after some specific size. In Finland, for example, bankruptcy statistics show that the risk of bankruptcy is the lowest in very small firms and in large firms but higher in middle-sized firms (Statistics Finland).

4. Empirical Results

4.1 Descriptive Statistics

The number of qualified observations is presented in Table 1 by country. For most countries, the number is high and sufficient for reliable statistical estimation with validity testing. There are no problems with the number of non-failed firms but the number of failed firms is small especially for Greece (estimation data 17 & test data 11) and Lithuania (36 & 16). The number of failed firms is below 100 in the estimation and hold-out data also for Bosnia & Herzegovina, Bulgaria, Malta, Serbia, and Slovenia. In these countries, special attention should be paid to consider the generalization of the results. For all countries, the estimation data includes 56541 failed firms and

3.4 million non-failed observations. These data are used to estimate the uniform prediction model over all 30 countries in the sample.

Table 2 shows the median values for the explanatory variables by country. For the return on assets ratio, the highest median for non-failed firms is found in Finland. However, this country reports the lowest median for failed firms showing a wide dispersion. The quick assets to total assets ratio has its highest median for non-failed firms in Sweden and almost as high in Germany. In Poland, the median of the ratio for failed firms is lowest and very low also for Russia. Estonia shows the highest median of the equity ratio for non-failed firms while Poland reports the lowest median for failed firms. The size of non-failed firms as measured by total assets is largest in Netherlands, Germany, and Ireland. In Greece and Ireland, the median size of failed firms is exceptionally large. In addition, the difference in median size between non-failed and failed firms can be positive or negative depending on the country. The median of the volatility measure is higher for failed than for non-failed firms in most countries, reflecting associated risk to fail. For non-failed firms the median is the highest for Estonia that also reports highest median for failed firms. Thus, the differences in the ratios between the European countries are large both for the non-failed and failed firms. This heterogeneity of the data makes the estimation of a reliable uniform model technically challenging.

Table 1. Number of qualified observations by country

	Estimation Data		Test Data	
Country	Non-failed	Failed	Non-failed	Failed
Belgium (BE)	251474	4174	108376	1768
Bosnia & Herzegovina (BA)	20311	62	8781	27
Bulgaria (BG)	64809	73	28264	30
Croatia (HR)	91019	419	39281	184
Czech Republic (CZ)	130658	808	56430	341
Denmark (DK)	19629	268	8340	118
Estonia (EE)	47731	338	20512	153
Finland (FI)	177056	1024	76208	432
France (FR)	225632	8673	96988	3765
Germany (DE)	140357	1516	60408	631
Greece (GR)	36013	17	15739	11
Iceland (IS)	22587	344	9895	154
Ireland (IE)	9466	180	3931	87
Italy (IT)	234256	11376	99860	4959
Latvia (LV)	11669	647	5052	271
Lithuania (LT)	4550	36	1899	16
Malta (MT)	6698	60	2918	28
Netherlands (NL)	25652	332	11247	147
Norway (NO)	256715	1969	110515	842
Poland (PL)	133455	439	57917	202
Portugal (PT)	250941	4786	108021	2056
Romania (RO)	51579	165	22334	80
Russian Federation (RU)	166644	3667	71878	1560
Serbia (RS)	70900	63	30716	28
Slovakia (SK)	34866	307	14969	146
Slovenia (SI)	19746	72	8696	30
Spain (ES)	189663	4244	81579	1796
Sweden (SE)	255651	3509	110096	1516
Ukraine (UA)	168948	2290	72672	991
United Kingdom (GB)	253818	4683	108767	2000
All countries	**3372493**	**56541**	**1452289**	**24369**

Table 2. Medians of the explanatory variables by country

	Return on assets ratio		Quick assets to total assets ratio		Equity ratio		Total assets		Semi-deviation of ROA	
	Non-failed	Failed	Non-failed	Failed	Non-failed	Failed	Non-failed	Failed	Non-failed	Failed
Belgium (BE)	2.50	-5.08	3.45	-23.74	31.58	3.09	0.36	0.29	0.03	2.25
Bosnia & Herzegovina (BA)	1.97	-2.38	-7.86	-11.94	38.22	0.00	0.46	1.38	0.05	0.32
Bulgaria (BG)	4.52	-1.20	-2.16	-5.88	33.66	6.45	0.54	1.26	0.00	0.85
Croatia (HR)	1.26	-1.33	-5.43	-25.39	21.64	0.00	0.31	1.15	0.19	0.11
Czech Republic (CZ)	2.72	-1.22	5.42	-35.64	37.46	-7.09	0.45	0.91	0.07	0.51
Denmark (DK)	1.84	-7.00	-8.37	-27.04	29.22	5.52	1.36	1.56	0.05	2.99
Estonia (EE)	4.02	-6.06	5.70	-27.28	53.89	12.03	0.22	0.57	0.61	6.23
Finland (FI)	5.63	-12.98	8.36	-33.28	44.47	-19.71	0.29	0.36	0.15	3.52
France (FR)	4.77	-1.68	2.41	-18.00	33.46	7.23	0.31	0.50	0.05	2.39
Germany (DE)	4.11	0.93	12.38	-2.54	25.12	7.11	5.40	1.41	0.00	0.00
Greece (GR)	1.32	-1.58	-0.51	-26.36	31.50	9.66	1.81	5.08	0.35	0.00
Iceland (IS)	0.16	-9.75	-1.79	-29.14	18.77	-10.34	0.23	0.43	0.23	4.86
Ireland (IE)	1.32	-2.53	3.52	-18.15	41.49	13.56	4.90	4.03	0.44	2.86
Italy (IT)	0.37	-4.82	-4.90	-36.15	15.09	-2.99	0.62	1.29	0.03	1.42
Latvia (LV)	4.04	0.42	-7.74	-20.67	25.95	8.05	0.77	0.72	0.34	1.99
Lithuania (LT)	3.47	-2.97	-1.92	-13.91	41.74	10.21	3.62	1.97	0.06	3.01
Malta (MT)	0.89	-0.18	-0.01	3.04	20.34	4.28	0.85	0.51	0.01	0.02
Netherlands (NL)	5.06	-2.64	7.96	-16.29	34.30	6.65	6.63	2.07	0.00	2.35
Norway (NO)	4.98	-6.48	6.74	-8.78	28.59	7.15	0.40	0.26	0.27	2.90
Poland (PL)	5.08	-1.38	2.35	-66.02	45.74	-53.57	0.85	1.34	0.01	0.60
Portugal (PT)	1.02	-4.32	-2.99	-27.04	25.48	2.73	0.30	0.53	0.09	1.06
Romania (RO)	4.75	-0.38	-8.71	-36.36	21.85	0.22	0.14	0.25	0.20	0.29
Russian Federation (RU)	2.73	-1.56	-9.06	-47.90	15.76	-5.37	0.40	0.43	0.00	0.38
Serbia (RS)	1.05	-2.28	-10.13	-21.59	27.94	0.00	0.27	2.62	0.31	0.00
Slovakia (SK)	2.24	-1.68	-4.35	-35.09	29.57	3.23	0.50	1.23	0.00	0.80
Slovenia (SI)	1.94	-0.25	-3.60	-12.28	30.18	8.65	0.99	1.27	0.09	1.13
Spain (ES)	0.89	-6.09	-4.00	-23.08	26.16	4.73	0.42	1.55	0.03	2.21
Sweden (SE)	4.52	-7.57	12.74	-17.02	43.10	8.07	0.28	0.21	0.10	3.67
Ukraine (UA)	0.04	-2.66	-6.52	-28.96	35.28	0.20	0.21	0.49	0.11	0.31
United Kingdom (GB)	3.49	0.15	8.06	-9.97	36.47	10.47	1.60	1.33	0.00	0.63
All countries	**2.37**	**-3.33**	**1.20**	**-25.00**	**30.63**	**2.38**	**0.42**	**0.65**	**0.02**	**1.41**
Average value	2.76	-3.22	-0.36	-23.41	31.47	1.34	1.18	1.23	0.13	1.65
Median value	2.61	-2.33	-1.85	-23.41	30.84	4.51	0.46	1.19	0.06	1.09

Specifications of the explanatory variables:

ROA = Return on Assets = *PLAT/TA**100

QUICK = Current Assets – Inventories – Current Liabilities

QUICKTA = Quick assets to total assets ratio = *QUICK/TA**100

EQTA = Equity Ratio = SHFD/TA

TA = Total Assets at the end of accounting period

TA^2 = (Total Assets)^2 = Total Assets * Total Assets

SV = Semi-deviation of return on assets ratio

where *PLAT* = Profit after Taxes (but before Extraordinary Items)

QUICK = Current Assets – Current Liabilities

SHFD = Shareholders' Funds

In case the shareholders' funds (book value of equity) is negative, the Total Assets of the balance sheet is replaced by the sum of all liabilities of firm. This adjustment applies to all variables in this study where *TA* is involved. As for *SV*, this measure of downside risk is calculated using the last two *ROA* observations. If the last (newer) figure is higher than the previous (older) one, then *SV* = 0. In calculating the *TA* and TA^2 variables, total asset values exceeding EUR 100 million were truncated to EUR 100 million.

4.2 Predictability of Failure

Table 3 shows the estimated rescaled coefficients of the logistic regression models by country. Since the observations are weighted, the significance levels have no standard interpretation and are upwards biased. Therefore, significance levels are not shown but coefficients with poorest significance are not disclosed. In order to facilitate interpretation, the coefficients are rescaled so that they are divided by the highest absolute coefficients in the sample.

Table 3. The estimated rescaled coefficients of the logistic regression models by country

Country	Intercept	Return on assets ratio (ROA)	Quick assets to total assets ratio	Equity ratio	Total assets	Total assets^2	Semi-deviation of ROA
Belgium (BE)	0.3522	-0.1132		-0.4552	-0.1186	0.0145	0.2266
Bosnia & Herzegovina (BA)		**-1.0000**	0.8231	-0.3657	**1.0000**	**-1.0000**	**-1.0000**
Bulgaria (BG)	0.5244	-0.4034	**1.0000**	-0.2761	0.1315	-0.0171	-0.3100
Croatia (HR)	0.1106	-0.2043	0.3646	-0.6884	0.2500	-0.0502	-0.1083
Czech Republic (CZ)	0.2458	-0.1264	0.0700	-0.5485	0.1202	-0.0235	
Denmark (DK)	0.9083	-0.3064	0.3515	**-1.0000**	0.0307	-0.0108	
Estonia (EE)	0.5019	-0.0193	-0.8231	-0.5616	0.2028	-0.0377	0.1352
Finland (FI)	0.2201	-0.1301	-0.2638	-0.6138	0.0227	-0.0097	0.0787
France (FR)	0.8116	-0.1109	0.5500	-0.6735		-0.0065	0.0901
Germany (DE)	0.9112	-0.0970	-0.2600	-0.4049	-0.1131	0.0180	
Greece (GR)	0.6003	-0.2704	**1.0000**	-0.5410	0.1234	-0.0202	-0.5743
Iceland (IS)		-0.0295		-0.2201			0.0528
Ireland (IE)			-0.6854	-0.1660			0.2529
Italy (IT)	-0.1995		-0.1100	-0.8078	0.1483	-0.0294	0.3282
Latvia (LV)	0.6425			-0.5019	-0.0807		
Lithuania (LT)	**1.0000**	-0.2807		-0.6511			0.1769
Malta (MT)		0.0467	0.5946	-0.1623			0.1809
Netherlands (NL)	0.8183	-0.0297	-0.4708	-0.3451	-0.1101	0.0131	0.1479
Norway (NO)	0.2500	-0.1176	0.3500	-0.2668	-0.0817	0.0125	0.1042
Poland (PL)	0.1518	-0.1719	-0.3015	-0.5784	0.0161	-0.0116	-0.0841
Portugal (PT)	0.3101	-0.2021	0.4269	-0.5448	0.1515	-0.0367	
Romania (RO)	0.2495	-0.0295	0.1715	-0.4515	0.5538	-0.3702	-0.0720
Russian Federation (RU)	-0.0421	-0.2050	-0.5285	-0.2985	-0.0197		-0.0422
Serbia (RS)		-0.4195	0.2546	-0.3638	0.4342	-0.0765	-0.6389
Slovakia (SK)	0.1699	-0.2292		-0.4030	0.1852	-0.0484	-0.0888
Slovenia (SI)	0.6754	-0.2322	0.6600	-0.6754	0.0817	-0.0135	0.2522
Spain (ES)	-0.1863	-0.3630	0.3185	-0.4515	0.3246	-0.0578	-0.1116
Sweden (SE)	0.8096	-0.0918	-0.3100	-0.5728	-0.1570	0.0239	0.1385
Ukraine (UA)	0.2682	-0.1021	0.1592	-0.2892	0.1143	-0.0219	-0.0693
United Kingdom (GB)	0.3000	-0.0217	-0.2115	-0.1515	-0.0260	0.0024	0.0834
All countries	**0.3329**	**-0.1043**	**0.0385**	**-0.4534**	**0.0313**	**-0.0082**	**0.0794**
Average value	0.4162	-0.1948	0.1252	-0.4677	0.1274	-0.0732	-0.0340
Median value	0.3101	-0.1301	0.1715	-0.4534	0.1143	-0.0186	0.0787

Note:

Coefficients are divided by the maximum absolute value over the countries

Coefficients with $p > 0.0001$ are not presented

The absolute maximum value (1.0000) is printed in bold

The model estimated for Bosnia & Herzegovina has the highest absolute coefficients for four variables. Lithuania has the highest absolute intercept reflecting the level of failure risk when all explanatory variables are equal to zero. Bulgaria and Greece have highest absolute coefficients for quick assets to total assets ratio but the coefficients imply, contrary to intuition, that risk is positive in the ratio. For the equity ratio, Denmark has the highest absolute coefficient in comparison to other countries. In each country, the equity ratio has a negative coefficient as expected. The sign of the return on assets ratio is also negative for all countries except for Malta. It is remarkable that the quick assets to total assets ratio has, against expectations, a positive coefficient more often than a negative one. This may be due to multicollinearity in the models. In the same way, the coefficients for total assets, squared total assets and semi-deviation are found to be either positive or negative.[3] The table also shows the coefficients of the uniform model that is estimated using the data from all countries. In this model, the quick to total assets ratio and total assets both have a low positive coefficient. The coefficients for other explanatory variables are of about the same magnitude as the median coefficients.

Table 4. Performance of country-specific logistic regression models in estimation data

				Correctly (%) classified	
Country	R-square	Max-rescaled R^2	AUC	Non-failed	Failed
Belgium (BE)	0.2281	0.3042	0.7870	73.24	70.87
Bosnia & Herzegovina (BA)	0.3562	0.4750	0.8616	76.21	79.03
Bulgaria (BG)	0.2369	0.3158	0.7846	73.74	65.75
Croatia (HR)	0.3120	0.4160	0.8412	78.11	78.28
Czech Republic (CZ)	0.3079	0.4106	0.8297	76.08	74.38
Denmark (DK)	0.3368	0.4491	0.8514	75.77	77.97
Estonia (EE)	0.3201	0.4268	0.8370	72.65	79.88
Finland (FI)	0.4010	0.5347	0.8817	80.67	81.05
France (FR)	0.2224	0.2965	0.7900	73.30	70.64
Germany (DE)	0.1682	0.2243	0.7445	65.30	73.28
Greece (GR)	0.2326	0.3102	0.7769	75.02	70.59
Iceland (IS)	0.0934	0.1245	0.6788	62.69	65.99
Ireland (IE)	0.1229	0.1638	0.7188	70.43	65.56
Italy (IT)	0.3152	0.4203	0.8347	84.68	65.44
Latvia (LV)	0.1421	0.1895	0.7184	62.61	69.24
Lithuania (LT)	0.3224	0.4299	0.8439	76.09	77.78
Malta (MT)	0.0611	0.0815	0.6519	66.32	58.33
Netherlands (NL)	0.2355	0.3140	0.7855	72.47	69.88
Norway (NO)	0.1349	0.1799	0.7201	74.28	63.66
Poland (PL)	0.4503	0.6004	0.9004	86.84	79.95
Portugal (PT)	0.2193	0.2924	0.7815	74.62	66.01
Romania (RO)	0.1847	0.2463	0.7525	67.23	69.70
Russian Federation (RU)	0.2358	0.3145	0.7836	72.34	69.18
Serbia (RS)	0.3162	0.4217	0.8459	79.60	76.19
Slovakia (SK)	0.2310	0.3080	0.7811	71.92	69.06
Slovenia (SI)	0.2129	0.2838	0.7870	72.27	73.61
Spain (ES)	0.2744	0.3658	0.8198	79.83	68.61
Sweden (SE)	0.2900	0.3867	0.8267	73.58	77.94
Ukraine (UA)	0.1480	0.1974	0.7262	64.55	68.34
United Kingdom (GB)	0.0713	0.0950	0.6669	64.09	64.28
All countries#	**0.2132**	**0.2843**	**0.7770**	**70.35**	**71.84**
Average value	0.2395	0.3193	0.7870	73.22	71.35
Median value	0.2341	0.3121	0.7863	73.44	70.24

Note:

= uniform model for all countries

Table 4 shows the performance of the country-specific logistic regression models in estimation data. The variation in performance between countries is large supporting the first research hypothesis (H1). The highest max-rescaled R^2 is found for Poland and also the model estimated for Finland performs exceptionally well. Malta and United Kingdom have got the lowest values, reflecting poor strength in dependence. The interpretation of other performance measures is in line with these results. Poland and Finland have the highest values for ROC and also for binary classification accuracy. The models estimated for Malta, United Kingdom, and Iceland show the lowest overall performance in classification.[4] The average AUC over the countries is about 0.79, referring to highly satisfactory performance given the considerably heterogeneous data. The uniform model utilizing data from each country (the "All countries" row in the table) gives an AUC of 0.78, being close to the average. For this model, the percent of correctly classified firms is over 70% for both non-failed and failed firms. Overall, the estimation results imply that it is possible to develop a reliable uniform model to assess failure risk in a large group of European countries, supporting the second research hypothesis (H2).

Table 5. Areas under the ROC curves (AUC) in test data for different countries

Applied to the Data			Model Estimated from Data of the Country																											
of the Country	All	BE	BA	BG	HR	CZ	DK	EE	FI	FR	DE	GR	IS	IE	IT	LV	LT	MT	NL	NO	PL	PT	RO	RU	RS	SK	SI	ES	SE	UA	GB
Belgium (BE)	**0.79**	**0.79**	0.71	0.71	0.77	0.78	0.79	0.76	0.79	0.79	0.78	0.70	0.79	0.76	0.78	0.78	0.79	0.61	0.78	0.79	0.78	0.78	0.74	0.78	0.70	0.77	0.79	0.76	0.79	0.77	0.78
Bosnia & Herzegovina (BA	**0.69**	0.66	**0.82**	0.75	0.70	0.69	0.70	0.64	0.68	0.69	0.66	0.72	0.68	0.58	0.67	0.67	0.69	0.56	0.63	0.68	0.69	0.70	0.72	0.68	0.75	0.71	0.69	0.73	0.65	0.70	0.64
Bulgaria (BG)	**0.63**	0.60	0.73	**0.81**	0.67	0.64	0.64	0.62	0.62	0.63	0.58	0.68	0.62	0.57	0.62	0.58	0.63	0.61	0.57	0.62	0.62	0.67	0.63	0.62	0.71	0.68	0.66	0.72	0.58	0.68	0.58
Croatia (HR)	**0.83**	0.76	0.73	0.75	**0.84**	0.84	0.82	0.81	0.81	0.82	0.76	0.80	0.83	0.73	0.83	0.79	0.80	0.63	0.74	0.75	0.81	0.84	0.82	0.78	0.80	0.84	0.82	0.82	0.76	0.84	0.76
Czech Republic (CZ)	**0.83**	0.80	0.79	0.78	0.83	**0.83**	0.82	0.83	0.82	0.81	0.80	0.78	0.83	0.81	0.83	0.80	0.82	0.63	0.80	0.79	0.82	0.83	0.81	0.82	0.80	0.83	0.82	0.83	0.80	0.83	0.81
Denmark (DK)	**0.84**	0.82	0.74	0.72	0.76	0.81	**0.85**	0.77	0.84	0.83	0.83	0.72	0.84	0.80	0.80	0.81	0.84	0.63	0.81	0.82	0.84	0.80	0.70	0.84	0.68	0.78	0.83	0.74	0.82	0.76	0.82
Estonia (EE)	**0.83**	0.81	0.72	0.71	0.82	0.83	0.82	**0.84**	0.83	0.82	0.82	0.69	0.83	0.82	0.84	0.82	0.82	0.58	0.82	0.78	0.82	0.82	0.82	0.81	0.73	0.82	0.81	0.80	0.82	0.82	0.83
Finland (FI)	**0.89**	0.88	0.82	0.81	0.88	0.88	0.88	0.88	**0.89**	0.88	0.88	0.82	0.88	0.86	0.88	0.72	0.88	0.68	0.88	0.87	0.88	0.88	0.86	0.88	0.82	0.88	0.88	0.86	0.88	0.87	0.88
France (FR)	**0.79**	0.82	0.78	0.72	0.78	0.78	0.79	0.76	0.78	**0.79**	0.77	0.72	0.78	0.74	0.78	0.78	0.78	0.61	0.77	0.78	0.78	0.78	0.76	0.77	0.71	0.77	0.79	0.76	0.78	0.77	0.77
Germany (DE)	**0.72**	0.73	0.61	0.55	0.63	0.67	0.73	0.63	0.72	0.72	**0.74**	0.61	0.71	0.68	0.68	0.73	0.73	0.56	0.72	0.72	0.73	0.66	0.59	0.73	0.52	0.64	0.69	0.57	0.73	0.62	0.73
Greece (GR)	**0.60**	0.56	0.46	0.73	0.64	0.61	0.60	0.62	0.59	0.60	0.55	**0.66**	0.60	0.55	0.60	0.57	0.60	0.63	0.53	0.56	0.58	0.63	0.49	0.57	0.70	0.66	0.61	0.69	0.56	0.65	0.57
Iceland (IS)	**0.73**	0.71	0.67	0.67	0.73	0.73	0.72	0.73	0.73	0.73	0.72	0.69	**0.78**	0.70	0.73	0.72	0.72	0.55	0.72	0.70	0.73	0.72	0.71	0.72	0.68	0.72	0.71	0.71	0.72	0.72	0.72
Ireland (IE)	**0.72**	0.79	0.67	0.63	0.70	0.71	0.71	0.71	0.71	0.71	0.67	0.62	0.70	**0.71**	0.72	0.68	0.72	0.58	0.68	0.67	0.71	0.72	0.68	0.71	0.62	0.72	0.72	0.69	0.68	0.69	0.70
Italy (IT)	**0.83**	0.80	0.76	0.74	0.82	0.83	0.83	0.82	0.83	0.81	0.80	0.72	0.83	0.80	**0.83**	0.80	0.82	0.65	0.79	0.77	0.83	0.82	0.79	0.82	0.77	0.82	0.82	0.81	0.80	0.82	0.81
Latvia (LV)	**0.72**	0.71	0.66	0.64	0.70	0.71	0.72	0.70	0.72	0.72	0.72	0.67	0.71	0.68	0.70	**0.72**	0.72	0.55	0.71	0.70	0.73	0.71	0.68	0.72	0.64	0.70	0.70	0.67	0.72	0.70	0.71
Lithuania (LT)	**0.77**	0.78	0.67	0.63	0.71	0.74	0.77	0.70	0.77	0.79	0.79	0.69	0.76	0.72	0.74	0.80	**0.77**	0.72	0.78	0.78	0.78	0.73	0.72	0.76	0.59	0.70	0.75	0.66	0.79	0.73	0.77
Malta (MT)	**0.57**	0.57	0.52	0.56	0.55	0.56	0.57	0.54	0.55	0.59	0.54	0.55	0.58	0.55	0.59	0.57	0.55	**0.68**	0.55	0.57	0.53	0.56	0.55	0.51	0.51	0.54	0.59	0.55	0.55	0.55	0.54
Netherlands (NL)	**0.71**	0.74	0.63	0.57	0.65	0.68	0.71	0.66	0.72	0.72	0.74	0.60	0.70	0.72	0.69	0.74	0.72	0.59	**0.75**	0.72	0.72	0.68	0.60	0.72	0.53	0.67	0.69	0.61	0.75	0.64	0.74
Norway (NO)	**0.70**	0.71	0.69	0.68	0.68	0.69	0.70	0.67	0.70	0.70	0.70	0.63	0.69	0.68	0.68	0.69	0.71	0.57	0.70	**0.72**	0.69	0.70	0.64	0.71	0.65	0.70	0.71	0.69	0.70	0.68	0.70
Poland (PL)	**0.91**	0.90	0.84	0.81	0.89	0.90	0.91	0.89	0.91	0.91	0.91	0.86	0.91	0.89	0.90	0.91	0.91	0.71	0.90	0.89	**0.91**	0.90	0.88	0.90	0.83	0.90	0.90	0.87	0.91	0.89	0.90
Portugal (PT)	**0.77**	0.75	0.75	0.74	0.78	0.78	0.78	0.75	0.76	0.77	0.74	0.74	0.77	0.72	0.77	0.75	0.77	0.62	0.73	0.76	0.76	**0.79**	0.76	0.75	0.75	0.78	0.78	0.78	0.74	0.78	0.74
Romania (RO)	**0.75**	0.74	0.71	0.71	0.74	0.74	0.75	0.73	0.74	0.74	0.73	0.71	0.74	0.69	0.74	0.73	0.74	0.54	0.72	0.73	0.74	0.75	**0.72**	0.73	0.72	0.75	0.74	0.74	0.74	0.74	0.73
Russian Federation (RU)	**0.77**	0.77	0.74	0.71	0.76	0.77	0.77	0.76	0.78	0.76	0.78	0.70	0.77	0.76	0.76	0.77	0.78	0.57	0.77	0.76	0.78	0.76	0.72	**0.79**	0.72	0.77	0.76	0.75	0.77	0.75	0.78
Serbia (RS)	**0.72**	0.60	0.81	0.63	0.79	0.76	0.72	0.69	0.69	0.70	0.60	0.80	0.72	0.51	0.72	0.61	0.67	0.57	0.53	0.62	0.69	0.78	0.77	0.65	**0.85**	0.79	0.74	0.82	0.84	0.79	0.57
Slovakia (SK)	**0.73**	0.69	0.73	0.73	0.75	0.74	0.73	0.74	0.73	0.71	0.69	0.71	0.73	0.71	0.73	0.69	0.72	0.56	0.69	0.68	0.73	0.75	0.74	0.73	0.75	**0.76**	0.73	0.76	0.69	0.75	0.70
Slovenia (SI)	**0.67**	0.68	0.70	0.66	0.64	0.65	0.68	0.61	0.66	0.69	0.65	0.61	0.66	0.63	0.64	0.65	0.68	0.63	0.65	0.69	0.66	0.67	0.64	0.65	0.61	0.65	**0.68**	0.65	0.66	0.64	0.66
Spain (ES)	**0.77**	0.71	0.78	0.78	0.79	0.78	0.77	0.76	0.75	0.75	0.70	0.72	0.77	0.72	0.77	0.69	0.75	0.63	0.68	0.71	0.74	0.79	0.76	0.74	0.78	0.80	0.79	**0.81**	0.70	0.79	0.71
Sweden (SE)	**0.82**	0.82	0.73	0.72	0.80	0.81	0.82	0.80	0.82	0.82	0.82	0.70	0.82	0.80	0.81	0.82	0.82	0.59	0.82	0.80	0.82	0.81	0.76	0.82	0.71	0.80	0.80	0.78	**0.83**	0.80	0.82
Ukraine (UA)	**0.72**	0.69	0.70	0.69	0.73	0.72	0.72	0.71	0.72	0.71	0.70	0.71	0.71	0.68	0.71	0.70	0.71	0.60	0.69	0.69	0.72	0.72	0.72	0.71	0.72	0.73	0.71	0.72	0.70	**0.73**	0.69
United Kingdom (GB)	**0.66**	0.67	0.60	0.55	0.63	0.64	0.66	0.63	0.66	0.66	0.66	0.57	0.65	0.65	0.65	0.66	0.67	0.54	0.67	0.66	0.66	0.64	0.62	0.66	0.55	0.63	0.64	0.60	0.67	0.62	**0.67**
Mean	**0.75**	**0.74**	**0.71**	**0.70**	**0.74**	**0.74**	**0.75**	**0.73**	**0.74**	**0.75**	**0.73**	**0.70**	**0.75**	**0.71**	**0.74**	**0.73**	**0.74**	**0.61**	**0.72**	**0.73**	**0.74**	**0.75**	**0.71**	**0.74**	**0.70**	**0.74**	**0.74**	**0.73**	**0.74**	**0.74**	**0.73**
AUC Uniformity		**-0.01**	**-0.13**	**-0.18**	**-0.02**	**0.00**	**-0.01**	**-0.01**	**0.00**	**-0.01**	**-0.02**	**-0.06**	**-0.05**	**0.01**	**0.00**	**-0.01**	**0.00**	**-0.11**	**-0.04**	**-0.02**	**0.00**	**-0.01**	**0.02**	**-0.02**	**-0.14**	**-0.03**	**-0.01**	**-0.05**	**-0.01**	**-0.01**	**-0.01**

Note:

AUC = 0,78 for all observations pooled (in test data)

AUC Uniformity = the difference between AUC for the uniform model and AUC for the country-specific model

Table 6. Correct classifications (%) and uniformities in test data.

	Uniform model				Country model				Uniformity in classification accuracy: Uniform model - Country model			
Applied to the Data of the Country	[1] Non-failed	[2] Failed	[3] Mean of [1] and [2]	[4] Average of [1] and [2], observation weights	[5] Non-failed	[6] Failed	[7] Mean of [5] and [6]	[8] Average of [5] and [6], observation weights	[9] Non-failed, [1] - [5]	[10] Failed [2] - [6]	[11] Mean of [9] and [10]	[12] Average, observation weights [4]-[8]
Belgium (BE)	72,8	70,9	71,9	72,8	73,1	71,8	72,5	73,1	-0,3	-0,9	-0,6	-0,3
Bosnia & Herzegovina (BA)	76,9	55,6	66,3	76,8	77,2	74,1	75,7	77,2	-0,3	-18,5	-9,4	-0,3
Bulgaria (BG)	74,8	56,7	65,8	74,8	74,1	80,0	77,1	74,1	0,7	-23,3	-11,3	0,6
Croatia (HR)	61,7	87,5	74,6	61,8	77,3	79,4	78,4	77,3	-15,6	8,1	-3,8	-15,5
Czech Republic (CZ)	72,5	76,3	74,4	72,6	75,9	73,6	74,8	75,9	-3,4	2,7	-0,4	-3,4
Denmark (DK)	74,5	79,7	77,1	74,5	75,8	78,0	76,9	75,8	-1,3	1,7	0,2	-1,3
Estonia (EE)	81,4	61,4	71,4	81,2	73,5	79,1	76,3	73,6	7,9	-17,7	-4,9	7,7
Finland (FI)	76,7	85,0	80,9	76,8	80,7	82,2	81,5	80,7	-4,0	2,8	-0,6	-4,0
France (FR)	76,7	65,0	70,9	76,3	73,2	71,6	72,4	73,1	3,5	-6,6	-1,6	3,2
Germany (DE)	68,4	64,7	66,6	68,4	65,0	71,3	68,2	65,1	3,4	-6,6	-1,6	3,3
Greece (GR)	76,3	54,6	65,5	76,3	74,5	36,4	55,5	74,5	1,8	18,2	10,0	1,8
Iceland (IS)	54,1	82,5	68,3	54,6	63,8	76,6	70,2	64,0	-9,7	5,9	-1,9	-9,5
Ireland (IE)	73,8	52,9	63,4	73,3	72,6	59,8	66,2	72,3	1,2	-6,9	-2,9	1,0
Italy (IT)	53,9	87,4	70,7	55,5	84,7	65,9	75,3	83,8	-30,8	21,5	-4,7	-28,3
Latvia (LV)	68,1	65,3	66,7	68,0	61,6	71,6	66,6	62,1	6,5	-6,3	0,1	5,9
Lithuania (LT)	84,0	37,5	60,8	83,7	76,6	68,8	72,7	76,5	7,4	-31,3	-12,0	7,1
Malta (MT)	59,9	64,3	62,1	60,0	66,1	53,4	59,8	66,0	-6,2	10,9	2,4	-6,0
Netherlands (NL)	75,4	60,5	68,0	75,2	72,6	66,7	69,7	72,6	2,8	-6,2	-1,7	2,6
Norway (NO)	74,5	63,1	68,8	74,4	74,3	63,7	69,0	74,2	0,2	-0,6	-0,2	0,2
Poland (PL)	82,4	84,2	83,3	82,4	87,4	80,2	83,8	87,4	-5,0	4,0	-0,5	-5,0
Portugal (PT)	68,1	72,2	70,2	68,2	74,6	67,3	71,0	74,5	-6,5	4,9	-0,8	-6,3
Romania (RO)	63,7	75,0	69,4	63,8	67,0	67,5	67,3	67,0	-3,3	7,5	2,1	-3,2
Russian Federation (RU)	56,8	76,3	66,6	57,2	75,9	69,0	72,5	75,8	-19,1	7,3	-5,9	-18,5
Serbia (RS)	66,7	67,9	67,3	66,7	76,7	89,3	83,0	76,7	-10,0	-21,4	-15,7	-10,0
Slovakia (SK)	69,0	64,4	66,7	68,9	71,8	63,7	67,8	71,7	-2,8	0,7	-1,1	-2,8
Slovenia (SI)	78,5	50,0	64,3	78,4	72,6	60,0	66,3	72,6	5,9	-10,0	-2,1	5,8
Spain (ES)	65,9	74,3	70,1	66,1	79,9	67,0	73,5	79,6	-14,0	7,3	-3,4	-13,5
Sweden (SE)	81,2	68,5	74,9	81,0	73,2	77,9	75,6	73,3	8,0	-9,4	-0,7	7,8
Ukraine (UA)	63,7	68,6	66,2	63,8	64,9	69,0	67,0	64,9	-1,2	-0,4	-0,8	-1,1
United Kingdom (GB)	72,2	51,7	62,0	71,9	64,4	63,6	64,0	64,4	7,8	-11,9	-2,1	7,5
All countries	**70,4**	**72,1**	**71,3**	**70,5**								
Mean of all countries	70,8	67,5	69,2	70,8	73,4	69,9	71,7	73,3	-2,6	-2,4	-2,5	-2,5

Table 5 presents the AUC figures in test data when a model estimated for a country is applied to each country's data. The average AUC is over 0.70 for each country except for Malta (0.61) (see the row entitled “Mean” close to the bottom of Table 5.). The highest average values of AUC (0.75) are obtained by models estimated using data from Denmark, France, Iceland and Portugal. The second column of the table shows the AUC values when the uniform model is applied to the test data sets of various countries. It shows that the uniform model performs best in Poland (0.91) and Finland (0.89), the average of these AUC values being 0.75. When the AUC by the uniform model is calculated using all test data observations in the study, the AUC becomes 0.78.

The model gives the lowest AUC for Malta, Greece, Bulgaria and United Kingdom. The bottom row of the table shows a measure of AUC uniformity that reflects the difference between AUC for the uniform model and AUC for the country-specific model. The uniformity gets its lowest values for Bulgaria, Serbia, Bosnia & Herzegovina and Malta. For most countries the measure is close to zero, which implies that the uniform model performs as well or nearly as well as the country-specific model estimated from the country data.

Table 6 allows comparing the correct classification rates for failed and non-failed firms by country. The table shows that the uniform model classifies correctly, on the average, over 70 percent of both failed and non-failed observations in Europe. A large negative figure in the uniformity section of Table 6 indicates that the uniform model performs poorly in classifying non-failed (column 9) or failed firms (column 10) for that country. For example, the uniformity of -23.3 for Bulgaria in column 10 indicates that as the uniform model succeeds to classify only 56.7% (see column 2) of the Bulgarian failures correctly, the model estimated using Bulgarian own data is able to correctly classify 80.0% of these failures (see column 6). These kinds of uniformity figures, being exceptional, suggest that some country-specific factor affects the classification performance. The reason could be accounting, cultural, legal factors etc., or that the definition of default is essentially different than for the majority of the other countries in the data. There are also cases (for example, Italy) when a large negative (positive) uniformity for failed firms is accompanied by a large positive (negative) uniformity for the non-failed firms. This means that the two cutoff-points are different in the sense that the uniform and country-specific models, when applied in a credit decision context with the same cutoff-value (for example, 0.5), could lead to very different accept/reject decisions. These kinds of situations are not necessarily indicative of poor classification ability per se, as is reflected in the acceptable Italian AUC’s (0.83) for both the uniform and country-specific models in Table 5.

The validation results in the test data thus confirm the research hypothesis that the predictability significantly varies between countries (hypothesis H1) but that it possible to develop a uniform failure prediction model with high overall classification accuracy (by the AUC criterion) for most European countries (hypothesis H2).

4.3 Explaining Differences between the Countries

The study shows that there are significant differences between the countries in the statistical distributions of financial predictors and in the form and performance of country-specific models. It can be expected that the differences in this variables technically affect the performance of the uniform model for all countries. Appendix 1 shows descriptive statistics for these variables. It also shows the Pearson correlation coefficient between the explanatory variables and AUC of the uniform model. The highest correlation coefficient is found for country-specific AUC in the test data. High correlation coefficients are also found for other performance measures of the country-specific models. Table 7 shows the results (final step) for the linear stepwise regression analysis where AUC of the uniform model in each country for the test data is explained by the estimation data medians of the predictors in failed and non-failed firms, the number of firms in the sample, the coefficient estimates of the country-specific logistic regression models, and the AUC of these models both in the estimation and the test data. The table shows that the model explains 92.4% of the variation in AUC between the countries. First, the most significant variable explaining country-specific differences in the test data AUC of the uniform model is the test data AUC of the country-specific model. The higher is the predictability for the country-specific model, the higher it is also for the uniform model. Second, the coefficient of the semi-deviation in the country-specific models has a significant positive effect on the uniform model AUC. Many countries have a negative sign for the coefficient which is against expectations (the theory) diminishing the performance of the uniform model.

Table 7. Final stepwise linear regression model explaining AUC in test data for the uniform model by country

Variable	Coefficient	Std. Error	Beta coefficient	t-test	p-value
Intercept	0.0630	0.0500	0.0000	1.259	0.2220
Country model: AUC in test data	0.7410	0.0700	0.6120	10.538	0.0000
Country model coefficient: semi-deviation	0.8730	0.1200	0.4600	7.255	0.0000
Quick assets to total assets ratio: median for failed	-0.0020	0.0000	-0.4040	-7.007	0.0000
Country model coefficient: intercept	0.0610	0.0140	0.2310	4.477	0.0000
Country model coefficient: total assets^2	-3.5580	0.9400	-0.2460	-3.787	0.0010
Country model: number of non-failed firms in estimation data	0.0000	0.0000	0.1960	3.734	0.0010
Country model coefficient: equity ratio	-0.1550	0.0600	-0.1240	-2.577	0.0180
R^2	0.9420				
Adjusted R^2	0.9240				

Third, the lower quick assets to total assets ratio for failed firms, the higher is the uniform model AUC. The variations in this ratio between the countries are large. For example, Malta shows a positive median ratio for failed firms but a negative ratio for the non-failed firms, and, consequently, AUC is very low. Fourth, the higher the intercept estimate in the country-specific model, the higher is the uniform model AUC. This result refers to the fact that the level of failure risk is at different level in different countries. Technically, this problem can be solved by country dummies. Fifth, the higher the coefficient of squared total assets, the lower is AUC showing the size effect on failure risk differs with respect to countries. Sixth, the higher the number of non-failed firms in estimation data, the higher is AUC. This number directly refers to the weight of the country in the overall estimation of the uniform model explaining the result. Seventh, the lower is the coefficient of equity ratio, the higher is AUC. Since the coefficient in the country-specific models is negative, the result means that the more weight equity ratio has in the model, the better is the performance of the uniform model. The absolute value of the coefficient is very small for example in Malta and the UK, which also show a very low AUC.

For the usefulness of the uniform model it is very important that the absolute difference between the uniform model AUC and the country-specific model AUC (absolute AUC uniformity) is small for countries. If this absolute uniformity is high, country-specific model should be used in failure prediction. Appendix 2 shows the correlation coefficients between the uniformity and the same country-specific variables as in Appendix 1. High correlation coefficients are found especially for the coefficients of the country-specific models (except for the equity ratio). Table 8 shows the (final step) results for the stepwise regression analysis where uniformity is explained by the country-specific variables. The final step only includes two country-specific variables which together explain 57.6% of the variation in uniformity. First, the higher the coefficient of semi-deviation in the country-specific model, the higher is uniformity. This result is as above due to the fact that many countries have a negative coefficient against the expectations diminishing uniformity. Malta, for example, has the highest absolute coefficient that is negative and, consequently, the lowest uniformity. Second, the lower the median quick assets to total assets ratio for failed firms, the higher is uniformity. This result can again be explained by the large variation in the ratio distributions between the countries. Malta is a good example for inconsistencies in these distributions (see above).

Table 8. Final stepwise linear regression model explaining AUC uniformity in test data for all countries

Variable	Coefficient	Std. Error	Beta coefficient	t-test	p-value
Intercept	-0.0600	0.0110	0.0000	-5.3470	0.0000
Country model coefficient: semi-deviation	0.7540	0.1370	0.6660	5.5120	0.0000
Quick assets to total assets ratio: median for failed	-0.0010	0.0000	-0.4050	-3.3480	0.0020
R^2	0.6060				
Adjusted R^2	0.5760				

4.4 Classification of Countries

The country-specific models behave in the similar way if they give similar predictive results when applied to the data from different countries. This similarity of country-specific models was assessed by the factor analysis applied to the test data AUC given by each model for each country. Thus, the factor analysis deals with 30 variables (country-specific models) and 30 observations (AUC of the country-specific model for each country). Appendix 3 shows the Varimax-rotated factor solution for these data. The Varimax rotation was used to make the factors independent of each other and to maximize the variation between the resulted classes or groups. The results clearly showed that there are only 2 significant factors which together explain 91.7% of the total variation in country-specific AUC estimates. Thus, on the basis of the largest loading the countries can be classified into two classes. In overall, the two factors explain well the variation in AUC for each country as is shown by the communalities. However, the percent of variance explained for Malta is only 10.2%. Thus, Malta is a very exceptional country with respect to failure prediction behavior in the present sample of 30 countries. Some countries have got high loadings for both factors so that their membership of any group is not strong (Czech Republic, Estonia, Portugal, Romania, and Slovenia).

For the first factor, the highest loadings have got by Netherlands, United Kingdom, Germany, Belgium, and Ireland in this order of magnitude. For the second factor, Serbia, Spain, and Greece show the highest loadings. The grouping based on the loadings can be compared with Laitinen (2002) for rating models, and Nobes (1983) and Doupnik & Salter (1993) for financial reporting systems, to the degree in which these studies include same countries. If the grouping is compared with Laitinen (2002), the first group is quite similar except for Spain which belongs to the second group in this study. The other groups are not similar. In Laitinen's grouping Denmark, Finland, and Sweden belong to the second group while they are members of the first group in the present classification. When compared with Nobes (1983) classification, all European countries in his first group ("micro-fair-judgmental" and "commercially-driven") and second group "macro-uniform", "government-driven", and "tax-dominated") belong to the first group in this grouping, except for Spain that belongs to the second group. Doupnik & Salter (1993) classification only includes European countries which in the present grouping belong to the first group, except for Portugal and Spain from the second group. These countries Doupnik and Salter classify to the fifth group together with Denmark, France, Italy, and Norway. Five of their groups include European countries. Thus, the grouping based on failure prediction behaviour is different from that of financial rating (of technology firms) and reporting. It may be that traditional differences in accounting practices are converged and do not anymore significantly affect international comparability of firms from different countries.

However, the differences in prediction model behaviour between the groups can be technically traced back to the differences in statistical distributions of financial predictors and in the form and performance of country-specific models. Table 9 presents descriptive statistics of these variables for the two groups. There are several statistically significant differences between the groups. First, the median quick assets to total assets ratio for non-failed firms is on average negative and very low in the second group. Second, the median coefficient of semi-deviation in the country-specific models is negative and thus against expectations. Third, the median coefficient of quick assets to total assets ratio is on average positive in the second group which contradicts with expectations (from the theory). Fourth, the average of the median of semi-deviation for failed firms is significantly lower in the second group. Fifth, the coefficient of total assets is on average negative in the first group but positive in the second group. Thus, when assessing the similarity of prediction models over European countries, the role of quick assets and deviation in profitability should be carefully considered. In addition, the size effect may vary across countries, which deteriorates the comparability of models.

Table 9. Descriptive statistics for two groups of countries

	Group 1		Group 2			
	Mean	Std. Dev.	Mean	Std. Dev.	t-test#	p-value
AUC uniformity	-0.016	0.026	-0.060	0.066	2.029	0.069
Return on assets ratio: median for non-failed	3.182	1.673	1.905	1.556	2.067	0.052
Return on assets ratio: median for failed	-3.632	3.739	-2.389	1.674	-1.257	0.219
Quick assets to total assets ratio: median for non-failed	2.086	6.592	-5.266	3.051	4.174	0.000
Quick assets to total assets ratio: median for failed	-23.038	15.866	-24.169	9.411	0.244	0.809
Equity ratio: median for non-failed	32.636	10.633	29.130	5.573	1.185	0.246
Equity ratio: median for failed	0.650	15.302	2.723	3.352	-0.579	0.569
Total assets: median for non-failed	1.527	1.953	0.496	0.480	2.229	0.036
Total assets: median for failed	1.074	0.905	1.555	1.408	-0.983	0.344
Semi-deviation: median for non-failed	0.126	0.169	0.132	0.126	-0.115	0.909
Semi-deviation: median for failed	2.185	1.656	0.594	0.677	3.720	0.001
Country model coefficient: intercept	0.356	0.332	0.186	0.201	1.743	0.093
Country model coefficient: return on assets ratio	-0.014	0.013	-0.044	0.037	2.498	0.031
Country model coefficient: quick assets to total assets ratio	-0.001	0.005	0.006	0.005	-3.747	0.001
Country model coefficient: equity ratio	-0.026	0.012	-0.057	0.110	0.883	0.400
Country model coefficient: total assets	-0.003	0.050	0.175	0.149	-3.669	0.004
Country model coefficient: total assets^2	0.000	0.000	-0.005	0.009	1.700	0.123
Country model coefficient: semi-deviation	0.016	0.016	-0.044	0.049	3.788	0.004
Country model: standard R^2	0.234	0.109	0.251	0.064	-0.553	0.585
Country model: Nagelkerke R^2	0.312	0.146	0.335	0.085	-0.553	0.585
Country model: AUC in estimation data	0.782	0.071	0.797	0.044	-0.722	0.477
Country model: correct classification percent for non-failed	72.785	6.570	74.083	5.033	-0.599	0.555
Country model: correct classification percent for failed	71.446	6.387	67.058	14.523	0.912	0.382
Country model: AUC in test data	0.778	0.070	0.780	0.061	-0.046	0.964
Country model: number of non-failed firms in estimation data	119672.200	101694.488	97904.900	77981.586	0.649	0.523
Country model: number of failed firms in estimation data	2205.750	3089.758	1242.600	1856.860	1.062	0.298
Country model: proportion of failed firms in estimation data	1.631	1.371	0.760	0.781	2.211	0.036

Note: # = equal variances not assumed

5. Summary and Discussion

The first objective of the study was to analyse the predictability of financial distress across European countries based on two research hypotheses. This predictability was analysed for 30 European countries using estimation data from 3372493 non-failed and 56541 failed observations, extracted from ORBIS. The explanatory variables were selected referring to the bankruptcy theory. The logistic regression analysis showed that almost in each country an accuracy of at least 0.70, measured by AUC, can be reached supporting predictability in Europe. The second objective was to compare predictability across countries. The analysis showed that for a small number of countries the predictability of failure is not good (Iceland, Ukraine, United Kingdom, and Malta). However, in some other countries predictability is very high (Finland and Poland). Thus, the results showed that there are significant differences in the predictability of failure between European countries supporting the first research hypothesis. The third objective was to develop a generic uniform model to predict distress in each country. For the objective, a uniform model was estimated using the data from all countries. The uniform model performed well in the majority of countries in the sample. However, this model did not perform well in Malta, United Kingdom, Bulgaria, Slovenia, and Greece, reflecting their special nature of data. The model was very efficient in Poland and Finland. In many countries, the uniform model performed as well as the country-specific model by the AUC criterion. Thus, the study clearly shows that it is possible to develop a uniform model of failure prediction that results in high overall accuracy in almost all European countries.[5] This result evidently gives support to the second research hypothesis. Thus, a uniform prediction model can serve as a powerful tool for stakeholders interested in international comparison of risky firms.

The detailed analysis of predictability showed that there are two main factors which deteriorate the performance of the uniform prediction model over European countries. First, the concept of quick assets (liquidity) may have a different content in some European countries which led to results contradicting with expectations. Second, the concept of semi-variation (volatility of profitability) should be carefully analysed due to similar contradicting results. There are also minor factors deteriorating the performance of the uniform model. First, the level of risk in countries is different which weakens the reliability of the intercept coefficient. This problem can be solved by country dummies. Second, there are differences in the importance of equity ratio between the countries leading to difficulties to find a reliable coefficient over the countries. Third, the effect of size on the failure risk differs significantly between countries resulting in an unreliable coefficient for the size measure and its squared form. Fourth, it seems that differences between the countries are not due to the differences in financial reporting systems. Therefore, explanations for these differences should be searched from other factors, such as economic environment, company status classification and coding systems, legislation, and culture. The problems discussed in this research give hints for further research in developing a uniform model for a large set of countries. In addition, a useful line for future research would be to include more countries in the sample, such as Asian countries and the U.S. The results in this pioneering study strongly urge researchers to continue research on international comparability in failure research.

Acknowledgements

This study is a part of a project (Grant No 126630) financed by Academy of Finland. Financial support from Jenny and Antti Wihuri Foundation and Foundation for Economic Education (Liikesivistysrahasto) is gratefully acknowledged.

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APPENDICES

Appendix 1. Descriptive statistics of country-specific variables

			AUC in test data for all countries:	
	Mean	Std. Deviation	Correlation coefficient	p-value
AUC in test data for all countries	0.748	0.080	1.000	
Return on assets ratio: median for non-failed	2.756	1.720	0.236	0.105
Return on assets ratio: median for failed	-3.218	3.223	-0.470	0.004
Quick assets to total assets ratio: median for non-failed	-0.365	6.617	0.110	0.281
Quick assets to total assets ratio: median for failed	-23.415	13.882	-0.662	0.000
Equity ratio: median for non-failed	31.467	9.302	0.267	0.077
Equity ratio: median for failed	1.341	12.565	-0.524	0.001
Total assets: median for non-failed	1.183	1.677	-0.199	0.146
Total assets: median for failed	1.234	1.098	-0.330	0.038
Semi-deviation: median for non-failed	0.128	0.154	-0.023	0.452
Semi-deviation: median for failed	1.655	1.587	0.365	0.024
Country model coefficient: intercept	0.300	0.302	-0.010	0.480
Country model coefficient: return on assets	-0.024	0.027	0.108	0.284
Country model coefficient: quick assets to total assets	0.001	0.006	-0.491	0.003
Country model coefficient: equity ratio	-0.036	0.064	-0.282	0.066
Country model coefficient: total assets	0.056	0.125	-0.086	0.325
Country model coefficient: total assets2	-0.002	0.006	0.121	0.263
Country model coefficient: semi-deviation	-0.004	0.042	0.281	0.066
Country model: standard R^2	0.239	0.096	0.696	0.000
Country model: Nagelkerke R^2	0.319	0.128	0.696	0.000
Country model: AUC in estimation data	0.787	0.063	0.690	0.000
Country model: correct classification percent for non-failed	73.218	6.044	0.554	0.001
Country model: correct classification percent for failed	69.983	9.829	0.406	0.013
Country model: AUC in test data	0.779	0.066	0.803	0.000
Country model: number of non-failed firms in estimation data	112416.4	93657.949	0.340	0.033
Country model: number of failed firms in estimation data	1884.7	2745.537	0.261	0.082
Country model: proportion of failed firms in estimation data	1.341	1.263	0.150	0.214

Appendix 2. Correlation coefficients of country-specific variables with AUC uniformity in test data

	AUC uniformity	
	Correlation coefficient	p-value
AUC uniformity#	1.000	
Return on assets ratio: median for non-failed	0.203	0.141
Return on assets ratio: median for failed	-0.131	0.245
Quick assets to total assets ratio: median for non-failed	0.259	0.084
Quick assets to total assets ratio: median for failed	-0.402	0.014
Equity ratio: median for non-failed	0.109	0.284
Equity ratio: median for failed	-0.090	0.319
Total assets: median for non-failed	0.118	0.268
Total assets: median for failed	-0.197	0.148
Semi-deviation: median for non-failed	0.083	0.331
Semi-deviation: median for failed	0.273	0.072
Country model coefficient: intercept	0.190	0.157
Country model coefficient: return on assets ratio	0.582	0.000
Country model coefficient: quick assets to total assets ratio	-0.561	0.001
Country model coefficient: equity ratio	-0.121	0.262
Country model coefficient: total assets	-0.424	0.010
Country model coefficient: total assets2	0.348	0.030
Country model coefficient: semi-deviation	0.665	0.000
Country model: standard R^2	0.015	0.468
Country model: Nagelkerke R^2	0.015	0.468
Country model: AUC in estimation data	0.032	0.434
Country model: correct classification percent for non-failed	-0.037	0.423
Country model: correct classification percent for failed	0.086	0.326
Country model: AUC in test data	-0.035	0.426
Country model: number of non-failed firms in estimation data	0.567	0.001
Country model: number of failed firms in estimation data	0.316	0.045
Country model: proportion of failed firms in estimation data	0.283	0.065
Mean of uniformity	-0.0305	
Standard deviation of uniformity	0.0476	

Note:

AUC uniformity = the difference between AUC for the uniform model and AUC for the country-specific model

Appendix 3. Factor solution for country-specific AUC in test data

	Varimax-rotated factors			
Country	Factor 1	Factor 2	Communality	Group
Belgium (BE)	**0.945**	0.243	0.952	1
Bosnia & Herzegovina (BA)	0.353	**0.766**	0.712	2
Bulgaria (BG)	0.127	**0.830**	0.704	2
Croatia (HR)	0.559	**0.821**	0.987	2
Czech Republic (CZ)	**0.714**	0.691	0.987	1
Denmark (DK)	**0.846**	0.522	0.988	1
Estonia (EE)	**0.726**	0.652	0.951	1
Finland (FI)	**0.880**	0.469	0.995	1
France (FR)	**0.874**	0.473	0.988	1
Germany (DE)	**0.955**	0.270	0.984	1
Greece (GR)	0.315	**0.901**	0.910	2
Iceland (IS)	**0.827**	0.538	0.974	1
Ireland (IE)	**0.928**	0.254	0.925	1
Italy (IT)	**0.790**	0.591	0.974	1
Latvia (LV)	**0.919**	0.213	0.891	1
Lithuania (LT)	**0.892**	0.442	0.991	1
Malta (MT)	**0.252**	0.197	0.102	1
Netherlands (NL)	**0.971**	0.181	0.975	1
Norway (NO)	**0.922**	0.316	0.950	1
Poland (PL)	**0.873**	0.477	0.990	1
Portugal (PT)	0.651	**0.753**	0.991	2
Romania (RO)	0.563	**0.761**	0.896	2
Russian Federation (RU)	**0.889**	0.429	0.974	1
Serbia (RS)	0.062	**0.990**	0.984	2
Slovakia (SK)	0.554	**0.823**	0.984	2
Slovenia (SI)	**0.754**	0.642	0.981	1
Spain (ES)	0.303	**0.942**	0.978	2
Sweden (SE)	**0.800**	0.436	0.830	1
Ukraine (UA)	0.527	**0.842**	0.986	2
United Kingdom (GB)	**0.958**	0.255	0.983	1
Eigenvalue	16.411	11.105		
Total variance explained	54.705	37.016		
Cumulative (%)	54.705	91.721		

Notes:

1 Altman, Sabato, and Wilson (2010) show that adding non-financial variables (for example, auditing qualification information, industry insolvency rates, known legal actions to recover debts), when available, can considerably improve predictive accuracy. Chava and Jarrow (2004) find that industry grouping variables significantly affect both the intercept and slope coefficients in their forecasting equations.
Market variables, although useful in bankruptcy prediction of listed firms (see. e.g. Campbell, Hilscher, & Szilagyi, 2008), are not considered in this study, because the vast majority in our data set are private firms.

2 The authors screened several variables with alternative specifications from each of these financial dimensions, and found these particular formulations to perform best in preliminary tests.

3 The combined effect of the two size variables typically results in a local turning point in the relevant range of EUR 0 – 100 million. This size effect means that risk first increases with size, reaches its maximum impact, and then begins to decline with further increase in size (Total assets). Our all European model with all observations included reaches the maximum size-related risk when the amount of the firm's total assets is EUR 35.1 million. In country-specific models, when both size variables are significant, we usually find this kind of a local maximum (instead of a minimum) effect on risk in the relevant range, exceptions being Belgium, Germany, Netherlands, Norway and Sweden.

4 In ORBIS there are no UK firms coded with the status "Bankruptcy". Therefore, we chose firms from categories "active (receivership)" (1037 firms) and "inactive (in liquidation)" (3646 firms) to represent failed observations. Since the UK results are disappointingly poor (AUC being 0.67 with the UK model and 0.66 with the uniform model), we ran additional analyses for both of these categories with the UK data. We found that in the estimation sample, when only firms coded "in liquidation" are included as failed observations, the AUC of the model becomes 0.663, with correct rates 62.9% for non-failed and 64.3% for failed firms. Then, including only firms in receivership, the AUC rises to 0.745, and the correct classification rates increase to 67.2% for non-failed firms and to 70.6% for the failed ones. This suggests that the smaller set of firms in receivership represents failed firms better than the "in liquidation" set. It is worth noting that poor predictive results with UK data are not atypical in previous studies. For example, the test data AUC values ranged from 0.67 to 0.71 for the pure financial ratio based models that were estimated using large UK datasets in the study by Altman *et al*. (2010). (See also Keasey & McGuinness (1990) for earlier UK results.)

5 The mean test data AUC of all the 30 countries by the uniform model is 0.75 (Table 5), the mean ROC uniformity being -0.031. If only EU countries (23) are included in calculating the mean, the AUC remains at 0.75 but the ROC uniformity reduces a bit to -0.023. This suggests that the effect of EU criterion on the model performance is rather small. If, on the other hand, we include only countries that have a reasonable number of failed class observations (more than 50 in the test data) and that have the failure status coded as "bankruptcy" in the database (altogether 15 countries), AUC rises to 0.79 and the ROC uniformity becomes -0.012. This suggests that factors related to data quality, sufficient sample size and, especially, coherence in the definition of the dependent variable, are important in international modeling of failure risk. Finally, including only EU countries with status coded as "bankruptcy" and a reasonable number of failed observations (12 countries), the AUC further rises to 0.80, and at the same time the average ROC uniformity diminishes to -0.007.

