



Article

Cross-Country Application of Manufacturing Failure Models

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Abstract: The post-Altman models suffer from moral amortization. This paper asks whether models developed in one country can be applied in other economies. One of the characteristics of the prediction model is that a date drives the estimation. Thus, the estimated model based on one economy is not necessarily applicable to other economies. To verify such a statement, we carried out a literature review to identify the manufacturing models constructed during the last 30 years that were reported in reputable scientific journals. Our literature comprised 75 papers, and with the application of the citation count and citation mining, we selected a sample and traced the selected papers to the cross-country application. Our results indicated an existing gap in the cross-economy validation of existing manufacturing models. Our study has implications for policy, as the application of the prediction models to cross-economies' consolidated financial statements is biased.

Keywords: failure; bankruptcy; chapter 11; regression count; meta-analysis; literature review; manufacturing insolvency; prediction; citation mining

1. Introduction

This study asks whether failure prediction models developed in one country can be consistent with the data from another region. The issue of the prediction of corporate insolvency is still a valid question in the research area. Since Altman's pioneering study (Altman 1968), there are a tremendous number of models reported in the literature. The practical use of the Altman model is not in question; however, this group of models suffers from long-term instability, methodological issues in respect of estimation and sampling, and cross-country validation. This research deals with the latter issue.

This research issue is significant as the global economy is becoming more integrated and cross-dependent than it was at the time Altman presented his local model. Thus, its contribution to understanding model construction and application brings both the research community and professionals towards a better application of the prediction models.

We focus on the manufacturing sector, as limiting the study to one subset allows for better control on variables like type of industry, capital requirements, and type of supervision, which are difficult to control between models.

To address the research question, we applied a combination of narrative literature review, citation regression count for sample determination, and citation mining. We identified the research population based on a key terms search on the Web of Science (the WoS) database. We allowed a time window of 30 years. We referred to a single data source for the abstracts to assure the consistency of the data. Our results are robust in terms of the different sample specifications and citation source selection. Our findings indicate a research gap in terms of cross-country model validation.

This paper contributes both to the failure prediction literature and to meta-analysis. Firstly, the paper provides robust data on the manufacturing model discussion. Secondly, it identifies the research gap for further studies in respect of the cross-country validation of the manufacturing model. Thirdly it extends a previous citation count regression with citation mining.

The paper is structured as follows. Section 2 presents the significant literature; Section 3 introduces the materials and methods; Sections 4 and 5 show the results and robustness of the results, respectively; Section 6 discusses the results and concludes the paper.

2. Literature Review

Shareholders, managers, creditors, and business partners are all interested in extending the lifetime operation of a company. Therefore, to understand and predict company failure, a highly sophisticated method has been created and used. This has been an area of extensive research for over 50 years. Until now, the most well-known model is the Altman model (Altman 1968). Altman was the first to apply a multidimensional discriminant analysis to predict corporate bankruptcy. To date, many of his models have been released (Altman and Hotchkiss 2011; Altman 2018), verified (Grice and Ingram 2001; Reisz and Perlich 2007; Tomczak and Radosiński 2017), and modified (Altman et al. 2017). In addition to the Altman model, other models have also been developed for the manufacturing sector and for other economies, for example, Poland (Pawełek et al. 2016), the Czech Republic (Karas and Režňáková 2017), and the Slovak Republic (Siekelová et al. 2015). There are numerous syntheses of the failure prediction literature.

(Altman 1984) has presented a review of the development of discriminatory models. The author showed a historical outline of the development of research on discriminatory models until the end of the 1970s. In the early 1980s, (Scott 1981) offered a classification of the methodological research into statistical models and those based on the theory of bankruptcy. (Dimitras et al. 1996) developed a literature review covering the period from 1932 to 1994, with the authors focusing on 47 scientific articles presenting predictive models for industrial enterprises. (O'Leary 1998) described the development of research on the application of artificial neural networks to bankruptcy prediction. In 2002, numerous syntheses of the bankruptcy research literature appeared, (Calderon and Cheh 2002) extended O'Leary's discussion on the use of neural networks in an assessment of the risk of failure and crime. (Tay and Shen 2002) presented a study on proxy collections. (Daubie and Meskens 2002, p. 79), synthesizing the discussion up to the end of the 20th century, believed that a better understanding of the causes of bankruptcy processes could lead to more favorable choices of variables used to identify problems and consequently give rise to better models.

(Bellovary et al. 2007) reviewed 165 models published after 1965, indicating that the average number of contained variables varies by around 10, with the accuracy of the model not related to them. They also drew attention to the trends prevailing in particular periods of research on bankruptcy prediction issues. While discriminatory analysis was the leading trend in 1960–1970, a decade later, between 1980 and 1990, researchers focused on logit models and neural networks. (Ravi Kumar and Ravi 2007) presented a review of statistical methods and artificial intelligence used in research on bankruptcy until 1968 to 2005. The authors pointed out that researchers used virtually all known statistical and artificial intelligence techniques to assess the risk of bankruptcy, and that current research on single models gives way to research on hybrid models using combinations of single models and artificial intelligence rules to identify optimal solutions. The 2007 financial crisis stimulated a renaissance of the credit risk and failure research.

Most recent reviews, like (Alaka et al. 2018) or (Shi and Li 2019), also do not address the issue of the cross-validation of the models. Thus, this indicates a technical research gap considered in this paper. As the presented review deals with the syntheses, the specific papers analysis will contribute actual evidence to the research knowledge base.

Following the initial literature review on bankruptcy prediction models, besides the Altman model, there are no common worldwide models developed and verified in one country and tested in another country. Therefore, this paper adopts the following working hypothesis:

Hypothesis 1 (H1). *Manufacturing insolvency models are reapplied on other economies.*

If this hypothesis is confirmed, the initial impression would not be justifiable. On the contrary, this would identify a research gap for further investigations.

3. Materials and Methods

We used the Web of Science Clarivate Analytics (the WoS) sociometric database as the primary population source. We searched the WoS according to the keyword “bankruptcy prediction model” and then “manufacture” and covered the period from 1990 to 2019. Population identification was carried out in December 2019. The identified population of 75 scientific articles met the selection criteria. The six unavailable papers were excluded from the population and an additional four papers were omitted as they do not refer to manufacturing. The final usable population consisted of 65 scientific papers. Detailed information can be found in (Supplementary Materials).

Selected methods used in the analyzed articles are given in Table 1. Mostly statistical techniques, such as multiple discriminant analysis (MDA), the logit model (LR), and probit model, were used in the analyzed papers and they are comparable with other methods. They are very easy to use but strict assumptions for the statistical approaches must be met to apply them, e.g., linearity, normality, and pre-existing functional forms relating criterion variables to predictor variables (Kim et al. 2018). In turn, artificial intelligence, e.g., neural network (NN) and support vector machine (SVM) methods are more complex, and in contrast to the statistical approach, they do not require advanced mathematical and statistical knowledge and do not need any assumptions (Horváthová and Mokrišová 2018).

Table 1. The list of methods used in the selected papers.

Period	Methods					
	MDA	LR	NN	SVM	DT	Other
2019–2010	23	17	8	7	6	20
2009–2000	8	3	2	3	0	11
1999–1990	0	1	0	0	0	1
Total	31	21	10	10	6	32

The metadata in the form of detailed variables were extracted from all papers which constitute the general population. The list of variables and their definitions are presented in Table 2.

In contrast to the original study presenting the methodology used (Staszkievicz 2019b), we applied the later version of the citation count model similar to that reported for the Baltic region review (Staszkievicz 2019a). A time-weighted number of citations was used as a dependent variable. The binary variables for Poland, Czech, Hungary, and Slovakia differentiate the Central Europe geographic area, while the Business and Economics variable filters the application area.

The following regression equation was applied:

$$TC/Year = \beta_0 + \beta_1 \times Publication_{Year} + \beta_2 \times Method + \beta_3 \times TimeSpan + \beta_4 \times Sample + \beta_5 \times R_{Czech\ Republic} + \beta_6 \times R_{Hungary} + \beta_7 \times R_{Poland} + \beta_8 \times R_{Slovak} + \beta_9 \times R_{Slovenia} + \beta_{10} \times Business \ \& \ Economics + \varepsilon, \tag{1}$$

where

β_i is the coefficient of the variable i and ε is the error term.

Table 2. The list of variables and their definitions.

Variable	Definition	Range
TC/Year	The number of citations divided by the number of years (in the denominator the year of publication is one)	$<0, +\infty$
Publication _{Year}	2019 + 1 minus year of publication natural number	$<1, +\infty$
Method	Binary variable value 1 for a survey using statistical methods, 0 in other cases	0 or 1
Sample	Size of the sample, the number was taken from each paper in the population (data extracted manually)	$<0, +\infty$
Period	The time range was taken from each study and the mean average analyzed research period in each paper	$<0, +\infty$
R _{Czech Republic}	Binary variable value 1 for the Czech Republic survey, 0 in other cases	0 or 1
R _{Hungary}	Binary variable value 1 for the Hungary survey, 0 in other cases	0 or 1
R _{Poland}	Binary variable value 1 for the Poland survey, 0 in other cases	0 or 1
R _{Slovak}	Binary variable value 1 for the Slovak Republic survey, 0 in other cases	0 or 1
R _{Slovenia}	Binary variable value 1 for the Slovenia survey, 0 in other cases	0 or 1
Business and Economics	Binary variable value 1 for the Business and Economics survey, 0 in other cases	0 or 1

The model estimates the average paper citation count. The model allows for identification of the leverage papers, used later for the citation mining in order to check the cross-validation of the manufacturing failure models.

Estimations were carried out using the ordinary least squares (OLS) with the correction of heteroskedasticity.

Based on the regression model, the leverage observation was identified, which indicates the heterogenic papers in the population (sample). Each paper (home paper) within the sample was reconciled to the external citation (host papers). The host papers were examined if the authors reapplied a model from the home paper on a different economy to that of the home paper. If so, the null hypothesis was rejected for the home paper.

4. Results

Table 3 shows the distribution of the population in Central Europe.

Table 3. Number of papers by country.

Country	Number of Articles
Czech Republic	12
Hungary	1
Poland	6
Slovak Republic	2
Slovenia	1
Unallocated	47
Total	65

In the whole population, there is only one paper that concerns all Central European countries, namely, Altman et al. (2017). An important part of the population are items that cannot be clearly attributed to the area. Descriptive statistics of the population are presented in Table 4.

Table 4. Descriptive statistics of the population.

Variable	Mean	Med.	Min.	Max.	5% Perc.	95% Perc.	Std. Dev.	Skew.	Kurt.	Mean
TC/Year	1.7	0.5	0.0	18.0	0.0	8.1	3.2	3.1	11.4	1.7
PublicationYears	7.2	6.0	1.0	28.0	2.0	16.0	5.2	1.7	3.6	7.2
Method	0.7	1.0	0.0	1.0	0.0	1.0	0.5	−0.9	−1.2	0.7
Period	7.7	5.0	0.0	50.0	1.0	18.0	8.3	3.0	11.8	7.7
Sample	53,026.9	475.0	0.0	3,191,734.0	4.0	27,909.0	395,467.1	8.1	64.9	53,026.9
R _{Poland}	0.1	0.0	0.0	1.0	0.0	1.0	0.3	2.9	6.5	0.1
R _{Czech Republic}	0.2	0.0	0.0	1.0	0.0	1.0	0.4	1.7	0.8	0.2
R _{Slovenia}	0.0	0.0	0.0	1.0	0.0	0.0	0.1	8.1	65.0	0.0
R _{Hungary}	0.0	0.0	0.0	1.0	0.0	0.0	0.1	8.1	65.0	0.0
R _{Slovak}	0.0	0.0	0.0	1.0	0.0	0.0	0.2	5.6	29.9	0.0
Business and Economics	0.7	1.0	0.0	1.0	0.0	1.0	0.5	−0.7	−1.6	0.7

The population variable is characterized by a relatively high variability. Table 5 presents the estimated model of the citation regression count together with model diagnostics.

Table 5. The results of the regression model.

Variables	Coefficient	Std. Error	t-Ratio	p-Value
const	2.25339	0.776356	2.903	0.0053 ***
PublicationYears	0.142455	0.0576817	2.470	0.0167 **
Method	−1.64165	0.801645	−2.048	0.0454 **
Period	−0.0175148	0.0342043	−0.5121	0.6107
Sample	$−6.27488 \times 10^{-6}$	3.64220×10^{-5}	−0.1723	0.8638
R _{Poland}	−0.760874	1.09228	−0.6966	0.4890
R _{Czech Republic}	−0.539631	0.805635	−0.6698	0.5058
R _{Slovenia}	40.0911	116.007	0.3456	0.7310
R _{Slovak}	−1.23644	2.29480	−0.5388	0.5922
Business and Economics	−0.495428	0.818482	−0.6053	0.5475
Model Diagnostics				
Mean dependent var		1.73	S.D. dependent var.	3.15
Sum squared resid.		250.67	S.E. of regression	2.13
R-squared		0.61	Adj. R-sq.	0.54
F(9, 55)		9.42	p-value(F)	1.69×10^{-8}
Log-likelihood		−136.10	Akaike criterion	292.20
Schwarz criterion		313.94	Hannan–Quinn	300.78

*** $p < 0.01$, ** $p < 0.05$. Model: OLS, using observations 1–65. Dependent variable: TC_Year. Heteroskedasticity-robust standard errors, variant HC1.

The model fit rates are not necessarily well-fitting, but this is not an obstacle to sample identification because the method is robust and depends primarily on the difference in the coefficients of the original model and the reduced model. Table 6 demonstrates the leverage points (articles) for which the value of the test statistic surpassed the reference point, while Table 7 shows the distribution by country.

The selected sample includes all the articles in multiple domains and all the control variables are represented, including articles not assigned to domains.

Table 6. Leverage papers.

No.	First Author	Error u	Leverage $0 \leq h \leq 1$	Year	Ref.
1	Altman, E.	0.4773	0.445 *	2018	(Altman 2018)
2	Altman, E.	0	1.000 *	2017	(Altman et al. 2017)
3	Siekelova, A.	-9.6782×10^{-16}	1.000 *	2015	(Siekelová et al. 2015)
4	Adeleye, T.	-0.13068	0.310 *	2013	(Adeleye et al. 2013)

* Leverage observation.

Table 7. Distribution of the leverage papers by country, areas, and citation count.

No.	First Author	Poland	Czech Republic	Slovenia	Hungary	Slovak Republic	Business and Economics	Citation WoS
1	Altman, E.	0	0	0	0	0	1	0
2	Altman, E.	1	1	1	1	1	1	54
3	Siekelova, A.	0	0	0	0	1	0	0
4	Adeleye, T.	0	0	0	0	0	0	6

5. Robustness of Results

The results provided earlier are subject to sampling bias due to the applied methodology. In order to verify the stability of the results, we applied an alternative approach both in terms of the sample selection and the source of the citations.

We cross-checked our results using the following procedure. Using the Google Scholar service, we compared the references of the sample to other papers and verified the potential application of the models developed in the sample (Table 8).

Table 8. Distribution of the leverage papers by country, areas, and citation count.

No.	First Author	Citation WoS	Citation Google Scholar	Cross-Validation
1	Altman, E.	0	2	Yes
2	Altman, E.	54	177	Yes
3	Siekelova, A.	0	0	No
4	Adeleye, T.	6	13	No

The cross-validation relates to the original Altman model. Diep, Tung, and Phung (Tung and Phung 2019) reapplied the Altman model on Vietnam’s economy.

The revised procedures do not affect our conclusion, except for the Altman model. None of the other models has been cross-applied on a third economy.

We then selected the random sample consisting of 10% of the revised population count and treated them as the home papers. Next, we replicated the host paper check (Table 9).

No cross-validation has been identified. None of the procedures affects our conclusion, and thus the results support the stability of the findings presented in Section 4.

Table 9. Robustness check random sample specification.

No.	First Author	Title	Year	Citation WoS	Cross-Validation	Ref.
1	M. I. Javaid	Efficacy of going concern prediction model for creditor oriented regime via liquidation	2018	0	No	(Javaid and Javid 2018)
2	B. Singh	Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies	2016	6	No	(Singh and Mishra 2016)
3	E. Rim	Classifying manufacturing firms in Lebanon: An application of Altman's model	2014	7	No	(Rim and Roy 2014)
4	J. K. Bae	Predicting financial distress of the South Korean manufacturing industries	2012	15	No	(Bae 2012)
5	K. Männasoo	Patterns of firm survival in Estonia	2008	11	No	(Männasoo 2008)
6	D. Faems	The effect of individual HR domains on financial performance: Evidence from Belgian small businesses.	2005	30	No	(Faems et al. 2005)

6. Discussion and Conclusions

The basic result of our analysis is that at the stage of the construction of the prediction models the verification (testing) sample is likely to include different economies (Altman et al. 2017), while subsequent cross-country validation by other authors than the original ones is infrequent. Our results indicate that most bankruptcy prediction models are built for a local purpose. It is rare, for example, that a model built and tested on Spanish data was also tested on Polish data. Researchers usually specify the details of models in the literature review. The Altman models are the exception. This observation supports the data dependency of the models. However, we are unable to fully reject our null hypothesis that “the manufacturing insolvency models are reapplied on other economies” as Altman models are reapplied across the world. Thus, we conclude that our results, besides the Altman models, indicate the lack of cross-border verification of the developed models.

The finding presented in this study extends the prior research syntheses of Altman (Altman 1984; Dimitras et al. 1996; O’Leary 1998; Calderon and Cheh 2002; Daubie and Meskens 2002; Bellovary et al. 2007; Ravi Kumar and Ravi 2007; Alaka et al. 2018; Shi and Li 2019) by identifying the need for cross-country validation of insolvency prediction models. The presented results do not conflict with any of the prior synthesis research but rather extend the context of failure research.

This study extends the (Staszkiwicz 2019a, 2019b) citation count methodology of population reduction with the mechanism of leverage papers citation mining. It allows to verify not only a paper directed hypothesis but also the derivatives hypothesis which relates to the paper’s literature impact. Contrary to prior research the fit of the regression count model is substantially higher than 20%, we understand this phenomenon to be the result of the homogeneity of the population in terms of the research issue. However, this study does not provide evidence to verify our understanding and it probably provides a good starting point for further extended research

Our approach is limited. The citation count regression does not pick up the most cited papers in a population, and thus the reference check suffers from the completeness risk. For example, (Harhoff et al. 1998) was cited 145 times, (Grice and Ingram 2001) 103 times, and (Ding et al. 2008) 128, however, these are relatively old papers published in 1998, 2001, and 2008, respectively. Another limitation of the presented approach is a publication bias. We searched for cross-country applications of the models, where the results may not necessarily be of sufficient importance to attract the audiences of the top tier journals indexed by the WoS. Due to the nature of the identification of the papers’

populations, some of the papers not closely related to manufacturing insolvency prediction were omitted (Staszkiwicz and Morawska 2019; Prusak et al. 2019; Karkowska 2019; Nocoń and Pyka 2019). The independent variables in the model follow the original methodology and are not standardized, nevertheless the methodology is less subjective than literature review based on researcher experience, and thus our conclusion remains most robust.

To conclude the research: this study identified a research gap in respect of the cross-country validation of the developed insolvency prediction models for the manufacturing industry. The findings are robust in terms of the different specifications of the sample selection methods. The identified gaps indicate a practical and systematic risk for the application of the prediction model in international companies. The centralization of risk management and risk model verification can result in a substantial model risk when models developed on local heterogenic data are used at the cross-national and cross-subsidiary level.

Supplementary Materials: The data for the regression count citation model calculation are available online at doi:10.17632/4nck5pg6b3.1.

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