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Enhancing Risk Management: A Comparative Study of Bankruptcy Prediction Models in Public Policy Contexts?

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A B S T R A C T

Risk Management become such an important study after 2008 Financial Crisis. As such the needs of research and improvement of Bankruptcy Prediction Models as risk assessment tool is a must. This paper will help the current and upcoming research in related fields in choosing best and suited variables and methodologies that can help revaluation and improvement bankruptcy prediction studies. This a quantitave research by using comparative associative model with non-parametric inferential analysis. To achieve the goal, this study involved four bankruptcy prediction models which two of them are commonly known models (Springate and Zmijewski) and another two are locally made by using data of Indonesia's. The result from data analysis of 1,860 samples shows that the locally made bankruptcy prediction model or more correctly the Herlina's Model came as the best performed model because by using suited data for certain economic and financial climate, bankruptcy prediction model can achieve a better result than commonly known models.

Key word: *Bankruptcy; Financial Distress; Forecasting; Public Policy*

1. INTRODUCTION

The bankruptcy prediction model refers to the process of calculating the probability of an entity's bankruptcy, especially for the public ones. Singh and Mishra (2019) classified bankruptcy prediction models into two groups, which first is parametric models that rely on financial and non-financial information, and second is non-parametric models that rely more into up-to-date information by using heavy calculation methodologies such as algorithms. The bankruptcy prediction model basically has two basic functions. First as an early warning in warding off business failures and second as an intermediary direct messenger to banks and other financial institutions in evaluating and selecting entities (Zopounidis & Dimitras, 1998).

The COVID-19 pandemic has indeed resulted in a fairly severe blow to the economy of Indonesia, but it couldn’t be said as a new thing when referring to the statement of the former Minister of Finance of the Republic of Indonesia 2013-2014, Mr. Chatib Basri where even though Indonesia's economic growth until 2019 was still around 5 %, but it is undeniable that Indonesia has been experiencing an economic slowdown. This statement was issued when referring to the GDP of Indonesia's expenditures which gradually declined from 2018 to the end of 2019. The same thing can also be seen from how the movement of Core Inflation which reflects Common Purchasing Power had stagnated at around 1% and below, while Producer Price Index had dropping drastically. This movement could be interpreted that businessmen took various ways to seize the market that didn’t have significant developments even by using strategy like lowering the selling price of their products in order to attract the existing market, and no longer glancing at market expansion strategy. It can be concluded that there is an economic slowdown due to sluggish public purchasing power, even before the COVID-19 pandemic.

Furthermore, it can also be seen from the point of view of the capital market and the financial resilience of Indonesian companies. As reported by Bisnis.com, there are 40 issuers on Indonesia Stock Exchange that are in danger of delisting from the stock floor (Gumilar, 2022). It can be said that the potential risk for delisting had increased rapidly from the previous only 24 issuers in 2021 (Soenarso, 2021) and 16 issuers in 2020 (Nursanti, 2020). Also reported from CNBC Indonesia news, PT Pemeringkat Efek Indonesia (Pefindo) warned of a decline in credit ratings for several issuers due to the downward trend in the performance of issuers on the IDX which could result in an increase in credit risk (Wareza, 2020). Then we can also look at the development of loan circulation by financial institutions in Indonesia to businessmen where there has been a downward trend in lending for working capital starting by 2019 rather than investment. If this is the case, it can be said that companies in Indonesia are securing their assets to protect their liquidation.

Risk management, especially from the aspect of loans and investment, where it is necessary to assess the risk and the possibility of the potential borrower or investee in failing to fulfill their obligations. At the micro level, bankruptcy is the main driver in increasing investment and loan risk. Therefore, a lack of exposure analysis understanding can lead to inaccurate usage of the right tools needed in risk analysis. This has been happened before with the 2008 financial crisis which resulted in a decline of credit and investment markets, which also resulted in declining of overall economic productivity. And if you look at the existing data on how the economic slowdown began in 2019, as well as the potential for delisting of issuers from the stock exchange which is increasing from year to year, it can be said that the financial resilience of companies in Indonesia is at a higher risk. As such, further improvement and research of the accuracy of bankruptcy prediction models are needed for banks and financial institutions.

Although needed, there is no doubt that bankruptcy prediction models had been experiencing some criticism for their relevance in predicting bankruptcy. Like what happened to the Discriminant Analysis (DA) model, which most common example is the Altman Z-Score model. Although it was easy to be developed and used by a large audience, the use of the DA model had been criticized because of its involvement in limited distributional assumptions where the assumptions used may be tainted by inappropriate sampling techniques (Lennox, 1999). This thing led many researchers to switch the methodologies from the DA model to logit models such as the Ohlson O-Score, by introducing the normality constraints. Lenox (1999) in re-evaluating the use of the DA, Logit, and Probit models revealed that first, cash flow and leverage have a non-linear effect in predicting bankruptcy, and second that the use of well-identified Logit and Probit models can be more accurate in carrying out their main objective rather than the DA model. Even so, the Logit model did not escape any criticism where the use of logit is said to be a model that still relies on the involvement of static variable characteristics and still untrustable to capture the entity's financial structure dynamically.

Tyler Shumway (2001) answered this criticism by introducing a Hazard model-based bankruptcy prediction model, where his bankruptcy prediction model also involves variables from the aspect of time and the current market condition (market-driven). However, a model that is too complex does not necessarily give satisfactory results. Fuertes and Kalotychou (2006) and Rodriguez and Rodriguez (2006) have another view where their research results show that complex models are more likely to provide more accurate predictions when sample testing is carried out, while more limited models produce more accurate predictions when used. for Ex-Post Periods analysis.

Giriūniene et al. (2019) explained that the involvement of macroeconomic aspects can increase the effectiveness of the bankruptcy prediction models. Majority of studies favor more Option Pricing-based bankruptcy prediction models like Shumway model over other bankruptcy prediction models (Bauer & Agrawal, 2014) (Mousavi, Ouenniche, & Xu, 2015) (Kozjak, estanj-Perić, & Besvir, 2014) (Wu, Gaunt, & Gray, 2010) (Xu & Zhang, 2009), but Binh, Trung, and Duc (2018) revealed another thing where bankruptcy prediction models that include accounting and macroeconomic aspects are better in carrying out their functions than those that only include aspects of market driven and macroeconomics only.

Different economic environments in fact could affect the accuracy and effectiveness of use of bankruptcy prediction models (Karas & Režňáková, 2014), which is also stated by Singh and Mishra (2016) also by Oz and Simga-Mugan (2018) where the commonly known bankruptcy prediction models are very sensitive to time periods as well as financial conditions and the business environment which is why re-testing, re-estimating, and reformulating the models are needed.

2. METHOD

This a quantitave research by using comparative associative model with non-parametric inferential analysis. This research will be involving nine general bankruptcy prediction models which are commonly known by researchers in accounting and management. The models are summarized in the following table 1:

Table 1. Tested Bankruptcy Prediction Models

Name	Formulas	Determination	Variables
Springate (S-Score)	$S = 1,03X_1 + 3,07X_2 + 0,66X_3 + 0,4X_4$	• (S > 0,862), entity will most likely not go bankrupt	

Name	Formulas	Determination	Variables
		• (S < 0,862), entity will most likely go bankrupt	• X1 = Working Capital to Total Assets (WCTA) • X2 = EBIT to Total Assets • X3 = EBT to Current Liabilities • X4 = Sales to Total Assets • X5 = ROA • X6 = Debt Ratio • X7 = Current Ratio • X8 = Debt to Equity • X9 = ROE • X10 = Operating Profit Margin • X11 = Assets Turnover
Zmijewski (X-Score)	$X = -4{,}3-4{,}5X_5+5{,}7X_6-0{,}004X_7$	• (X > 0), entity will most likely go bankrupt • (X < 0), entity will most likely not go bankrupt	
Herlina Murhadi Z-Score	$Zind = -3{,}569 + 6{,}910X_6 - 1{,}107X_8 + 7{,}515X_9 + 3{,}573X_{10}$	• ($Zind_1$ > -3,521), entity will most likely not go bankrupt • ($Zind_1$ < -3,521), entity will most likely go bankrupt	
Antikasari Djuminah Logit	$Yind = -15.751 + 0.812X_5 - 2.059X_7 + 31.127X_6 - 7.345X_{11}$	• (Yind < 0,50) entity will most likely not go bankrupt • (Yind > 0,50) entity will most likely go bankrupt	

Source: Various references processed (2022)

Springate and Zmijewski Models are commonly known, while Herlina Murhadi and Antikasari Djuminah are models that domestically developed in Indonesia.

Data set to be tested are entities that are currently “listing” and “delisting” at Indonesian Stock Exchange (IDX) for the period from 2018 to 2020. Firm that can be called as sample is the one that has all information needed to do calculation in bankruptcy prediction. Sample that eligible to be called as distressed must meet one of the following requirements:

A. Entity was declared “delisting” from IDX
B. Entity was suspended from trade in IDX
C. The entity had a negative equity condition
D. The entity had a negative net income for 2 years consecutive

To measure the effectiveness of the models, researcher will use classification method. The reason for this method is because researcher needs to evaluate how well the models in grouping the data. To do this, first researcher will put every bankruptcy model or to be called as classifier result into 2x2 contingency table called as “Confusion Matrix” like this:

Table 2. Confusion Matrix

		Firm Condition (Actual)	
		Not Distressed (0)	Distressed (1)
Classifer (Prediction)	Not Distressed (0)	True Positive (TP)	False Negative (FN)
	Distressed (1)	False Positive (FP)	True Negative (TN)

Source: Various references processed (2022)

After that we can calculate further findings to describe accuracy, F1 Score, MCC, and Brier Score. After that we can illustrate the wellness of each classifiers compared to others by using Receiver Operating Characteristics (ROC) Curve to measure the classifier’s performance from predictiveness aspect. The last analysis will be reliability test by using Kuder-Richardson 20 (KR-20). By doing this, we could see how consistent a bankruptcy prediction model in carrying out its function of providing a prediction within a certain time interval or period. The consideration of using KR-20 is because the data being tested is a dichotomous data that is in the form of only two values ("Predicted" or "Missed"). Further discussion of result will be discussed in three sections which are 1 Year Prior, 2 Years Prior, and Overall Result. All of these analyses are done by using R Programming Language with R-Studio 2022.02.3 Build 492 help.

Hypotheses

H_1: Re-estimated and / or Reformulated model has better performance than original static model.

We also need to consider whether the bankruptcy models are effective or not in term of usage and its function. Research by Grice and Dugan (2001) shows that the accuracy of bankruptcy prediction models are decreasing due to the differences in the samples that being used. Nyitrai (2019) stated that a statistical-based model can be a better model when using a dynamic sample. Madonna and Cestari (2015), also Rybárová, Majdúchová, Tetka, and Luščíková (2021), as well as Charalambakis and Garrett (2016) assessed that a model built specifically for an economic and financial business climate does not necessarily give the best results in predicting bankruptcy. however lefendorfas (2016) stated different opinion related to that.

H_2: Locally made bankruptcy prediction model has better performance than commonly known model

If we look back again at previous explanation, we can see how almost every researchers in bankruptcy tried to cancel each other. However, such thing is reasonable. Prediction or should be said forecasting in the context of statistics cannot produce absolute values. Main reason is because forecasting as a practice of estimating future events using past data, according to Sanders (2015) involves three basic principles in its procedural:

- The prediction process will be difficult to approach constant accuracy, due to factors in environment that cannot be predicted with certainty in the near future.
- The level of accuracy will be closer to the observation of a group rather than an individual.
- Prediction will show the result function when used for a shorter period of time.

Thus, it is why the needs to regularly testing bankruptcy prediction models with the aim of maintaining their effectiveness is a must. Bankruptcy prediction models cannot predict future events for the entities in absolute terms, especially when considering how the entity's external factors such as business environment can change at any time. However, this does not mean that bankruptcy prediction models are unusable. The reason is bankruptcy prediction model can be used as a risk measurement tool to help entity in preparing and anticipating possible economic events that can harm the entity, such as financial distress and bankruptcy occurring in the future. This research also can help to indicate whether the difference in economy and business condition between developed countries and developing countries can tell if is there a difference of how the business failure can occurred. Whether the models that was developed in developed country can applied in the developing country condition could help to answer this question. That is why researcher is using commonly known bankruptcy models and locally made bankruptcy models to find out the solution of that problem.

3. FINDINGS AND DISCUSSION

Result should be clear and concise. The results should summarize (scientific) findings

First researcher will present the summary of collected data for analysis.

Table 3. Summary of Data Set

	Population	Samples	Distressed	Not Distressed
1 Year Prior	1,243	1,221	299	922
2 Year Prior	575	556	145	411
Overall	1,882	1,860	389	1,471

Source: Secondary data processed (2022)

As seen by the table 3 for 1 year prior analysis, of 1,243 total population, researcher got 1,221 firm that are qualified as sample with 299 firms are in distressed position while 922 are not. For 2 year prior analysis, of 575 total population, 556 firms are taken as sample with 145 firms are in distressed position while 411 are not. Last for Overall which was data from year 2018 to 2020, researcher got 1,860 samples from 1,882 of total population with 389 firms are in distressed position while 1,471 are not. To be noticed that "Overall" data is not a sum of data for 1 year prior and 2 year prior. Now we can go further with accuracy findings, first it will be 1 year prior to distressed situation. We now can look at table 4 below.

Table 4. Prediction Result by Each Classifiers

	1 Year Prior				2 Year Prior				Overall			
	S	**X**	**Zind**	**Yind**	**S**	**X**	**Zind**	**Yind**	**S**	**X**	**Zind**	**Yind**
TN	279	116	125	116	128	50	55	56	365	166	186	165
TP	409	807	865	768	187	358	382	339	574	1,283	1,324	1,224
FN	20	183	174	183	17	95	90	89	24	223	203	224
FP	513	115	57	154	224	53	29	72	897	188	147	247
Accuracy	0.56	0.76	0.81	0.72	0.57	0.73	0.79	0.71	0.50	0.78	0.81	0.75
Brier Score	0.44	0.24	0.19	0.28	0.43	0.27	0.21	0.29	0.50	0.22	0.19	0.25
Precision	0.44	0.88	0.94	0.83	0.45	0.87	0.93	0.82	0.39	0.87	0.90	0.83
Recall	0.95	0.82	0.83	0.81	0.92	0.79	0.81	0.79	0.96	0.85	0.87	0.85
F1 Score	0.61	0.84	0.88	0.82	0.61	0.83	0.87	0.81	0.55	0.86	0.88	0.84
MCC	0.34	0.29	0.43	0.23	0.31	0.24	0.38	0.22	0.29	0.31	0.40	0.25
Error Type 1	0.65	0.50	0.31	0.57	0.64	0.51	0.35	0.56	0.71	0.53	0.44	0.60
Error Type 2	0.05	0.18	0.17	0.19	0.08	0.21	0.19	0.21	0.04	0.15	0.13	0.15

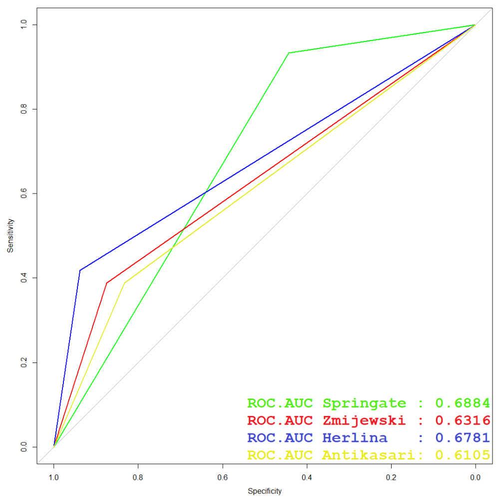
Source: Secondary data processed (2022)

As seen on table 4, we can assume that Herlina (Zind) Model is the best among all by looking at how the accuracy is the top among all classifiers (81%, 79%, and 81%)), and also with brier score that lowest apart from others (19%, 21%, and 19%). Precision of Herlina (Zind) is the one with the highest score too, but when we look at its Recall score, it's not the lowest among competing classifiers (Zmijewski (x) and Antikasari (Yind)) which is not looking good because when Precision is up, then

Recall must down to be called as a good predictor. But then again we can ignore of this result because the difference of its Recall score between the competing ones (Zmijewski (x) and Antikasari (Yind)) are pretty close and tight. To seek balance between Precision and Recall, we can look at F1 Score. Again, Herlina (Zind) Model came as the best among all by having highest score again. And in the Matthew Correlation Coefficient (MCC) we also can see that Herlina (Zind) is the one with the highest score. But it still couldn't pass the 0.50 score limit that means even when it has the highest one, the score is more towards random suggestion than agreement between prediction and actual. For the worst among all, we can clearly tell that Springate (s) are the one with the worst performance by looking at how its Accuracy, Brier Score, Precision, Recall, and F1 Score performed. But if we looking at MCC score, it came in second place than Zmijewski (x) and Antikasari (Yind) for 1 year prior and 2 year prior observation. Which mean Springate even came as worst classifier, moving apart from random suggestion better than Zmijewski (x) and Antikasari (Yind) for 1 year prior and 2 year prior observation. The exception is at Overall observation where its MCC score came third surpassed by Zmijewski (x). The prediction power of all classifiers are decreasing by time to time, as seen from 1 year prior observation to 2 year observation, which mean the expected result of prediction is lowered for further expected period of time.

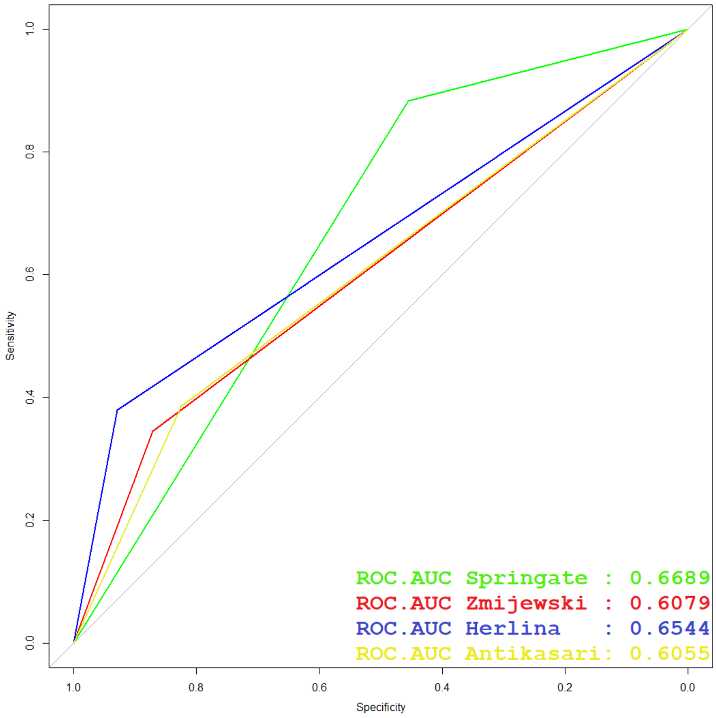
Next, we can visualize the performance of classifiers by using ROC curve. As seen on ROC curve below for 1 year prior and 2 year prior, we can assume that Herlina model perform better than rest by looking at how its line reaching Y Axis closer than others. But in term of Area Under Curve (AUC), the Herlina's is beaten by Springate's which mean that Springate model can distinguish distressed and not distressed firm better than Herlina's. What more interesting is at how both Zmijewski's and Antikasari's are having lower AUC score than Springate. This can indicate two different things. First, Springate has better ability to categorize whether the firm is saved or in distressed or second Springate can achieve better performance only for shorter time period. For overall result, which we don't consider whether the prediction will happen sooner or later, we can see that Herlina one achieved the best result among all both from how its graph line moving towards Y axis much closer and its AUC score is the highest one among others. By using that result, researcher can safely take that Hypothesis 1 (H_2) and Hypothesis 2 (H_1) are correct. But then again, this is not with some certain notes because if we consider the AUC aspect, no models can't achieve higher score than 0.7 which mean overall performance result of all models are poor if we consider the AUC values between 0.8-0.9 as good, 0.7-0.8 as fair, 0.6-0.7 as poor, and failed for AUC values between 0.5-0.6.

Figure 1. ROC Curve – 1 Year Prior



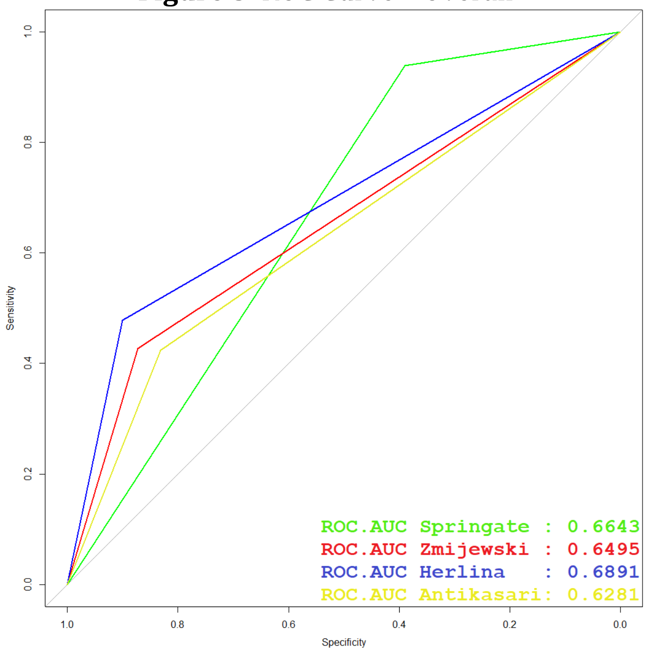
Source: Output R-Studio 2022.02.3 Build 492 (2022)

Figure 2. ROC Curve – 2 Year Prior



Source: Output R-Studio 2022.02.3 Build 492 (2022)

Figure 3. ROC Curve – Overall



Source: Output R-Studio 2022.02.3 Build 492 (2022)

Last, we will discuss the consistency of the prediction by each classifier by referring to table below.

Table 5. KR-20 Result by Each Classifiers

	1 Year Prior	2 Year Prior	Overall
S	0.505878	0.471776	0.4424
X	0.448181	0.392792	0.4735
Zind	0.595274	0.54363	0.5727
Yind	0.373699	0.363471	0.402

Source: Output R-Studio 2022.02.3 Build 492 (2022)

As seen by table 5, we can figure how consistent of each prediction giving its accurate result. Kuder-Richardson 20 (KR-20) score ranged from "0" to "1". "0" means inconsistent while "1" means stable consistent. By looking at table 5, we can see that Herlina (Zind) is giving a better result that consistent from time to time. Most interesting thing is happening again when considering the result of Springate (s) towards other models beside Herlina (Zind). In here we can see that Springate (s) has consistency performance much better than Zmijewski (x) and Antikasari (Yind) in 1 year prior and 2 year prior observation. Same like how we interpreted the ROC curve before, Springate (s) just beaten to third place at overall result.

Public Policy Framework

The article emphasizes the critical relationship between bankruptcy prediction models and public policy, particularly in the context of risk management. Here's a detailed explanation of how public policy impacts these models:

1. Regulatory Framework. Public policy creates the rules and regulations that govern business operations. This regulatory framework can significantly influence the financial health of companies. For example, policies that enforce transparency and accountability in financial reporting compel businesses to provide accurate and timely financial data. This improved data quality is crucial for bankruptcy prediction models, as they rely on historical financial information to assess the likelihood of a company's failure. When businesses adhere to stringent reporting standards, the inputs into these models become more reliable, thereby enhancing their predictive accuracy.

2. Economic Conditions. Public policies aimed at maintaining economic stability—such as fiscal policies (government spending and taxation) and monetary policies (interest rates and money supply)—directly affect the business environment. For instance, an increase in interest rates can raise borrowing costs for companies, potentially leading to financial distress. Conversely, tax incentives can stimulate business growth. Bankruptcy prediction models must be adaptable to these economic fluctuations; if they are based on outdated assumptions that do not reflect current economic conditions, their effectiveness in predicting bankruptcy will diminish. Therefore, models need to incorporate variables that account for these changing economic factors.

3. Support Mechanisms. Public policies that offer support to struggling businesses, such as bailouts, loan guarantees, or restructuring programs, can alter the risk landscape. When businesses believe they have a safety net, they may engage in riskier behavior, assuming that they will be rescued if they encounter financial difficulties. This perception can skew the

predictions made by traditional bankruptcy models, which typically do not factor in the potential for government intervention. As a result, models may need to be adjusted to consider the impact of such support mechanisms on business risk profiles.

4. Data Availability and Quality

Effective public policy can enhance the availability and quality of financial data through regulations that mandate improved reporting practices. When businesses are required to maintain high standards of financial disclosure, the data used in bankruptcy prediction models becomes more comprehensive and accurate. This is vital because these models depend on historical data to forecast future outcomes. Better data quality leads to more reliable predictions, allowing stakeholders to make informed decisions regarding risk management.

5. Cultural and Social Factors. Public policy also influences the cultural and social environment in which businesses operate. Policies that encourage entrepreneurship, innovation, and competition can create a more dynamic business landscape. In such an environment, traditional bankruptcy prediction models may need to evolve to account for new types of risks and opportunities that arise from innovative business practices. For example, the rise of technology startups may introduce different financial metrics and risk factors that were not previously considered in conventional models. Adapting to these cultural shifts is essential for maintaining the relevance and effectiveness of bankruptcy prediction models.

Public policy plays a pivotal role in shaping the effectiveness of bankruptcy prediction models. By establishing regulatory frameworks, influencing economic conditions, providing support mechanisms, improving data quality, and shaping cultural factors, public policy directly impacts how these models function. As such, it is crucial for researchers and practitioners to continuously evaluate and adapt bankruptcy prediction models in response to evolving public policies and economic realities to ensure they remain effective tools for risk management.

4. CONCLUSION

This paper is mainly to examine how well the domestic models performed compared to commonly known bankruptcy prediction models. The result of this research can conclude that by using suited data for certain economic and financial climate, bankruptcy prediction model can achieve a better result than commonly known models. Herlina model that achieved the best result among others seems proved it statement. Also by looking at how Springate model performed, researcher can conclude that how important to update and re-estimate the coefficient in the model by using the newer data. And also it seems that MDA analysis still a better methodology for probability analysis, especially in financial sector. This study can has same conclusion like the ones that has been done by Rybárová, Majdúchová, Tetka, and Luščíková (2021), as well as Charalambakis and Garrett (2016) if we not considering the AUC aspect.

The interplay between public policy and bankruptcy prediction models is significant. As the article suggests, regularly updating and reformulating these models to reflect current economic and regulatory conditions is essential for maintaining their relevance and effectiveness in predicting financial distress. This ongoing adaptation is crucial for policymakers and businesses alike, as it helps in making informed decisions that can mitigate risks associated with bankruptcy. Last, for future and similar research, researcher suggest to involve more broader methodology that also include reformulation of formula models and re-estimation of coefficient models with broader time periods data to achieve more certain result than this paper.

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