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Comparative Analysis of The Accuracy Level of The Zmijewski, Springate, and Grover Models to Predict Financial Distress

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ABSTRACT: Financial Distress is a stage in a company's financial downturn before bankruptcy or liquidation.The purpose of this study is to learn more about the Zmijewski, Springate, and Grover techniques' ability to accurately forecast financial difficulty in startups listed on the Indonesia Stock Exchange between 2019 and 2021.Descriptive quantitative research methodology is employed. Accuracy tests and descriptive statistical analysis are the analysis techniques used.The study's findings show that the Springate model, which has the highest accuracy rate of 81.81% and type I and type II error values of 18.18% and 0%.While the accuracy of the Zmijewski and Grover models is the same (69.69%), but the type I and type II error rates are different.

Keywords : *Financial Distress; Grover; Springate; Startup; Zmijewski.*

I. INTRODUCTION

The rapid growth of information and communication technology can increase trends and encourage the establishment of new businesses that tend to utilize technology (Pateli & Gigalis, 2005). This potential gave birth to several digital startups that continue to grow in the country by producing creative products and focusing on solving problems in everyday life (Permadi, 2017). Startups are newly established businesses that are still in development and research stage to find market potential, target markets and all things related to technology, information, and communication (Ries, 2011). Startups are required to be ready to enter the free market on the internet that can reach many consumers. In terms of the number of startups worldwide, Indonesia comes in sixth (Startup Ranking, 2022). As of July 2022, there are 39 unicorns in Southeast Asia, where Indonesia is in second place with 9 unicorns, including Gojek Tokopedia (GoTo), Bukalapak, J&T Express, Traveloka, Akulaku, Xendit, Ajaib, Kopi Kenangan, and JD.ID (Rizaty, 2022). Unicorns are startup companies that have a valuation of up to US$ 1 billion or equivalent to 14.1 trillion Rupiah (Mirawati, 2021).

Although startups experience development and growth in a positive direction, it is not uncommon for them to experience the dynamics in their operational activities. This is due to the high market competitiveness of services or products from startups that are the choice of consumers, funding, and poor management of financial statements that make it difficult for startups to grow (Gompers & Lerner, 2001). In addition, most startups also feel the impact of the crisis due to Covid-19 (Mulya, 2020). At the beginning of the Covid-19 pandemic, only 33% of companies were in good condition. Whereas before the pandemic, as many as 74.8% of companies had good company conditions. This is a manifestation of a significant decline in several company sectors.

However, there are some companies that continue to run and get a positive impact from the Covid-19 pandemic, especially startups in the fields of digital payments, logistics, and health. Meanwhile, startups that have experienced a negative impact from the pandemic are the tourism sector, due to social restrictions due to the pandemic. This impact has resulted in startups experiencing serious problems, namely layoffs (Kharisma, 2021). The peak is in 2022 where there is a phenomenon of mass layoffs carried out by several startups such as Zenius, Si Cepat, Ruang Guru, Shopee, Sirclo, GoTo and many more (Kompas, 2022). Yudistira (2022) stated that the causes of layoffs carried out by several startups include products losing competition; difficulty finding new funding; and economic uncertainty.

The rise of layoffs is one sign of financial distress in a company (Fahmi, 2012). If the financial distress that occured during the pandemic was not followed by strategic policies, it would result in the company going bankrupt. Therefore, financial distress must be taken into accountand known by company management, as early as possible in order to make the best decisions and avoid the risk of bankruptcy. A company is deemed to be in financial distress when it has two years of negative operating profit (Almilia & Kristijadi, 2003). Cashlez

Worldwide Indonesia Tbk, Kioson Commercial Indonesia Tbk, and Tourindo Guide Indonesia Tbk are three startup companies with negative profits over more than a yearbetween 2019 and 2021, according to financial information on statements from the Indonesia Stock Exchange (IDX).

Through the financial statement data, information will be analyzed and found that can determine the condition of the company. One type of financial statement analysis technique is through financial ratios. This is related to signaling theory, where the results of financial ratio analysis can be a signal that can be known from financial statements. This statement agrees with Ross (1977) who says that signaling theory is a signal from the company by providing certain information to external parties. Scott & Brigham (2008) state that the information referred to in signaling theory is about the company's prospects. This information will be analyzed to determine whether it is a good news signal or even a bad news signal (Rachmawati & Nur, 2021). These signals serve as a basis for investors in making investment decisions (Meitasari & Anwar, 2021).

In analyzing financial distress or the level of financial difficulty of a company, there are many measurement methods, such as Zmijewski, Springate, Grover and so on, which use financial ratios. Each financial distress prediction model's level of accuracy varies. Various financial distress models studies, it shows that there are inconsistencies in the results of the level of accuracy. The existing differences are caused because basically each model has its own characteristics. The aim of this study is to evaluate the analysis's findings and the precision of the prospective financial distress prediction model for startups listed on the IDX in the 2019–2021 timeframe utilizing Zmijewski, Springate, and Grover models.

II. LITERATURE REVIEW

2.1 Signaling Theory

Spence (1973) was the first to propose signaling theory. According to this notion, the information owner uses important information about the company's current situation to convey a signal to recipients or investors. The information referred to in signaling theory, according to Scott & Brigham (2008), is related to the company's future.

2.2 Agency Theory

Agency theory is a contract from one or more people who delegate agents to have the authority to make decisions so that ownership and management of the business are separate entities(Jensen & Meckling, 1976). In relation to this perspective, the shareholders' or the principal's contractual relationship gives the agent (company management) the authority to govern the business, including when making choices (Yuniningsih, 2017). The purpose of separating ownership and management of the company is so that the company owner gets optimal profit at the most efficient cost possible by managing the company by professional agents as shareholders. Meanwhile, shareholders only oversee the company's operations managed by agents and develop an incentive system so that they work in the interests of the company (Tandiontong, 2016).

2.3 Financial Report

According to Kasmir (2018), financial statements include details regarding a company's financial situation during a specific time period. The foundation for investing decisions is financial statements. In making a decision, a comparative analysis of financial statements for two or more periods is needed in order to produce more specific data.

2.4 Financial Distress

According to Platt & Platt (2002), financial distress is a stage in a company's financial downturn before bankruptcy or liquidation.The company will be in financial trouble if its cash flow from operations cannot cover its immediate liabilities (Wruck, 1990). If a corporation has negative net income for two years in a row and doesn't pay dividends for more than a year, it is in financial distress (Almilia & Kristijadi, 2003). Companies that experience the financial distress result in a loss of trust from stakeholders such as creditors and investors, and they will rethink the relationship with the company.

2.5 Zmijewski Model

Ratio analysis is a technique used by Zmijewski (1983) to evaluate a company's performance, leverage, and liquidity. The Zmijewski model that was successfully developed is:

$$X = -4{,}3 - 4{,}5X1 + 5{,}7X2 - 0{,}004X3 \qquad [2.1]$$

Description :

X1 = Return On Asset

X2 = Debt Ratio

X3 = Current Ratio

The ratio return on assets is used to assess how successfully a business generates money from its assets (Kasmir, 2009). The higher the current ratio, the less likely it is that the company would experience financial distress (Susilo & Suwaidi, 2022). Meanwhile, the debt ratio requires the company's income to exceed debt so that financial distress does not occur (Arohmawati & Pertiwi, 2021). According to Zmijewski (1984), financial difficulty is expected if the X value is greater than 0 or positive. Conversely, a company is expected not to have the potential to incur financial distress or be deemed healthy if it has a value that is less than 0 or negative. Zmijewski (1984) states that this model has an accuracy value of 94.9%.

2.6 Springate Model

The multidiscriminant analysis, also known as multiple discriminate analysis (MDA), was employed in the Springate model, which calculates ratios (Permana et al., 2017). According to Springate (1978), this model has a 92.5% accuracy rate for predicting bankruptcy. Four financial ratios are combined in a formula called the Springate Model, mathematically formulated as follows :

$$S = 1{,}03X1 + 3{,}07X2 + 0{,}66X3 + 0{,}4X4 \qquad [2.2]$$

Description :
X1 = Working Capital to Total Asset
X2 = Return On Asset
X3 = Earning Before Tax to Current Liabilities
X4 = Sales to Total Assets

A company's operational working capital as a percentage of its total assets is shown by the working capital to asset ratio (Riana & Diyani, 2016). If the company's net working capital is negative, it indicates that it will have trouble meeting its short-term obligations due to a lack of current assets. This allows financial distress to occur. The ratio of return on assets is used to assess how successfully a business generates money from its assets (Kasmir, 2009). The ratio of Earnings Before Tax to Current Liabilities reveals how well a company can operate while still making pre-tax earnings. While the sales-to-total-assets ratio demonstrates how well management uses all resources of the organization to drive sales and produce revenues (Hanafi & Halim, 2005). According to Springate (1978), there are two categories: If the S value is below 0.862, the company is in financial trouble and may experience bankruptcy. In the meantime, if S> 0.862, it means that the company's finances are sound (non-distressed).

2.7 Grover Model

In order to create a new bankruptcy prediction model, Jeffrey S. Grover reevaluated the Altman model in 2001.The sample utilized incorporates thirteen new financial ratios and is consistent with the Altman Z Score model from 1968. From 1982 to 1996, there were 70 companies with 35 going bankrupt and 35 being excluded from this study. The Grover (2001) model yields the following formula:

$$G = 1{,}650X1 + 3{,}404X2 + 0{,}016X3 + 0{,}057 \quad [2.3]$$

Description :
X1 = Working Capital to Total Assets
X2 = Earning Before Interest and Taxes to Total Assets
X3 = Return On Assets

The working capital to total assets ratio displays the amount of operational working capital relative to total assets for the company (Riana & Diyani, 2016). The ratio of Earnings Before Interest and Taxes to Total Assets gauges how productive an asset is at generating profits before interest and taxes are subtracted. A company's ability to create profits from its assets is gauged by its ratio of return on assets (Kasmir, 2009).Grover (2001) categorizes companies with a score of $G \leq -0.02$ as unhealthy or experiencing financial distress. The score for companies categorized as healthy is $G \geq 0.01$.

2.8 Conceptual Framework

The conceptual framework for thinking in this study can be organized as follows based on the problem's history and the theory's explanation :

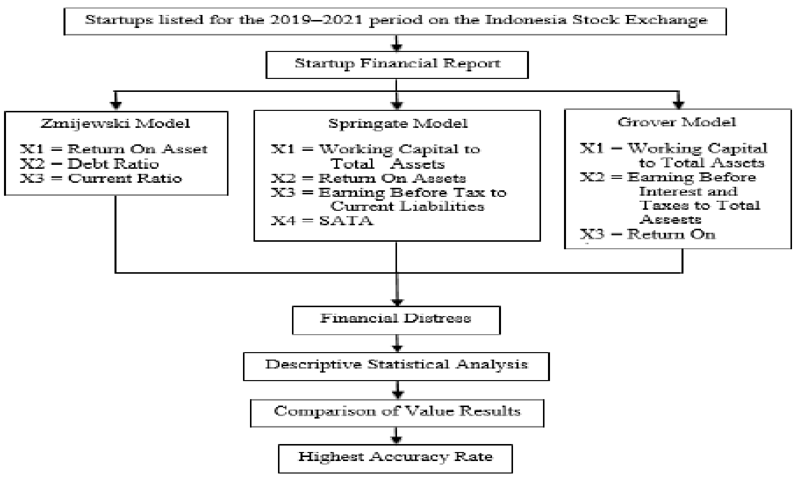

Figure 1. Conceptual Framework

III. METHODS

A total of 34 companies the Indonesia Stock Exchange's (IDX) IDXTECHNO index made up the population of this study. Purposive sampling, a nonprobability sample strategy with predetermined criteria, was utilized in this study to ensure that the data gathered was more representative. With a total of 33 research sample data, the study's samples consisted of 11 technology companies listed on the Indonesia Stock Exchange (IDX) for the 2019–2021 timeframe. This study uses secondary data which are in the form of annual financial reports of startups listed on the Indonesia Stock Exchange (IDX) in 2019-2021 obtained from the official website of the Indonesia Stock Exchange (IDX), namely www.idx.co.id.Descriptive statistical analysis techniques and testing of the predictive model accuracy are employed in this descriptive quantitative research methodology.

IV. RESULT

4.1 Zmijewski Model Calculation Results

Based on the appendix table of the results of the calculation of Financial Distress predictions, it can be seen that the calculation of financial distress using the Zmijewski model in startup companies in 2019-2021 there are two companies that are predicted to experience financial distress. The two companies are companies with the GLVA code in 2019 and KIOS in 2020. While other companies are predicted not to experience financial distress. This is based on the provisions (cut off) in the Zmijewski prediction model, namely the company will be declared healthy if the calculation results are <0, and vice versa the company will be declared unhealthy or potentially experiencing financial distress if the calculation results> 0.

4.2 Springate Model Calculation Result

It can be seen that the calculation of financial distress using the Springate model in startup companies in 2019-2021 there are two companies that are predicted to experience financial distress. The two companies are companies with the code CASH in 2019 and PGJO in 2019, 2020 and 2021. Meanwhile, other companies are predicted not to experience financial distress. This is based on the provisions (cut off) in the Springate prediction model, namely the company will be declared healthy if the calculation results> 0.862, and vice versa the company will be declared unhealthy or potentially experiencing financial distress if the calculation results <0.862.

4.3 Grover Model Calculation Result

It can be seen that the calculation of financial distress using the Grover model in startup companies in 2019-2021 all companies are declared healthy or not experiencing financial distress conditions. This is based on the provisions (cut off) in the Grover prediction model, namely the company will be declared healthy if the calculation results are> -0.02, and vice versa the company will be declared unhealthy or potentially experiencing financial distress if the calculation results are < -0.02.

4.4 Comparison of Financial Distress Prediction Model Calculation Results

The following is a comparison of the results of the calculation of financial distress predictions in startup companies listed on the Indonesia Stock Exchange (IDX) for the 2019-2021 period, using three prediction models :

Table 1. Comparison of Financial Distress Prediction Calculation Results

Model	Comparison Result		Sample Quantity
	Financial Distress	Non Financial Distress	
Zmijewski	2	31	33
Springate	4	29	33
Grover	-	33	33

Based on table 1, it can be seen that the calculation of financial distress in startup companies in 2019-2021 using the Zmijewski model resulted in two companies predicted to experience financial distress, the Springate model resulted in four company sample data predicted to experience financial distress, while the Grover model resulted in all companies being declared healthy or not experiencing financial distress.

4.5 Descriptive Statistical Analysis

Descriptive statistical analysis techniques are used to determine the minimum, maximum, mean and standard deviation values of the three financial distress prediction models of startup companies on the Indonesia Stock Exchange (IDX) during the 2019-2021 period. The results of descriptive statistical tests for each model can be seen in the following table:

Table 2. Descriptive Statistics of Financial Distress Prediction Model

Model	N	Minimum	Maximum	Mean	Standard Deviation
Zmijewski	33	-6,157	0,949	-2,585	1,436
Springate	33	-0,990	13,622	2,645	2,402
Grover	33	0,621	2,273	1,664	0,293

4.5.1 Descriptive Statistics of Zmijewski Model

Based on table 2, the results of financial distress predictions in startups on the IDX in 2019-2021 using the Zmijewski model have a mean value of -2.585.This interprets that the average of all startup companies sampled from 2019-2021 is classified as not experiencing financial distress (Zmijewski cut off score <0).

4.5.2 Descriptive Statistics of Springate Model

The mean value of the results of the calculation of financial distress predictions at startups on the IDX in 2019-2021 using the Springate model is 2.645, this interprets that the average of all startup companies sampled from 2019-2021 is classified as not experiencing financial distress (Springate cut off score> 0.862).

4.5.3 Descriptive Statistics of Grover Model

The mean value of the results of the calculation of financial distress predictions in startups on the IDX in 2019-2021 using the Grover model is 1.664, this interprets that the average of all startup companies sampled from 2019-2021 is classified as not experiencing financial distress (Grover cut off score ≥ 0.01).

4.6 Financial Distress Prediction Model Accuracy Test

The accuracy of the prediction model is used to test the accuracy of the group of companies experiencing financial distress and the group of companies that do not experience financial distress in each model. To measure the level of accuracy is as follows (Altman, 2000):

$$\text{Accuracy Level} = \frac{Total\ Correct\ Predictions}{Total\ Samples}\ \text{X}\ 100\%$$

Another consideration is the level of error that arises from each prediction model, which is divided into 2 types including (Altman, 2000):

Type I Error

Type I error is an error that occurs when the measurement model when predicting the sample produces no distress, but in fact experiences distress. The type I error rate can be calculated in the following way:

$$Type\ I\ Error = \frac{Total\ Type\ I\ error}{Total\ Sampel}\ X\ 100\%$$

Type II Error

Type II error is an error that occurs when the measurement model predicts the sample to experience distress, but in reality it does not experience distress. The type II error rate can be calculated in the following way:

$$Type\ II\ Error = \frac{Total\ Type\ II\ error}{Total\ Sampel}\ X\ 100\%$$

Data sample criteria for calculating the accuracy level of each model are :

Table 3. Accuracy Rate Calculation Sample Criteria

Category	Sample Criteria	Total
1	Negative net income	10
2	Positive net income	23
Total Sample		33

4.6.1 Accuracy Test of Zmijewski Model

The following are the results of calculating the accuracy of the Zmijewski model:

Table 4. Zmijewski Model Accuracy Calculation Results

	Total Sample	Correct Prediction	False Prediction	*Type Error*	
Distress	10	1	9	Type I	27,27%
Non Distress	23	22	1	Type II	3,03%
Total	33	23	10		
Accuracy Level	69,69%				

Based on table 4, the Zmijewski model can correctly predict 23 out of 33 samples with an accuracy rate of 69.69%. The remaining 10 out of 33 samples were predicted incorrectly. Type I error is 27.27%, reflecting that as many as 10 samples in the category of distressed companies, it turns out that from the prediction results of the Zmijewski model there is 1 sample data that is correctly predicted to be in financial distress. The remaining 9 sample data are predicted incorrectly. While the type II error is 3.03% which reflects that as many as 23 samples in the non-distressed company category, it turns out that from the prediction results of the Zmijewski model there are 22 sample data that are correctly predicted in non-financial distress conditions. The remaining 1 sample data is predicted incorrectly.

4.6.2 Accuracy Test of Springate Model

The following are the results of the calculation of the accuracy of the Springate model:

Table 5. Springate Model Accuracy Calculation Results

	Total Sample	Correct Prediction	False Prediction	*Type Error*	
Distress	10	4	6	Type I	18,18%
Non Distress	23	23	-	Type II	0%
Total	33	27	6		
Accuracy Level	81,81%				

Based on table 5, the Springate model can correctly predict 27 out of 33 samples with an accuracy rate of 81.81%. The remaining 6 out of 33 samples were predicted incorrectly. Type I error is 18.18%, reflecting that as many as 10 samples in the category of distressed companies, it turns out that from the prediction results of the Springate model there are 4 sample data that are correctly predicted to be in financial distress. The remaining 6 sample data are predicted incorrectly. While the type II error of 0% reflects that as many as 23 samples in the category of non-distressed companies, it turns out that from the prediction results of the Springate model managed to predict all non-distressed sample data correctly.

4.6.3 Accuracy Test of Grover Model

The following is the result of calculating the accuracy of the Grover model:

Table 6. Grover Model Accuracy Calculation Results

	Total Sample	Correct Prediction	False Prediction	*Type Error*	
Distress	10	-	10	Type I	30,30%
Non Distress	23	23	-	Type II	0%
Total	33	23	10		
Accuracy Level	69,69%				

Based on Table 6, the Grover model can correctly predict 23 out of 33 samples with an accuracy rate of 69.69%. The remaining 10 out of 33 samples were predicted incorrectly. Type I error is 30.30%, reflecting that as many as 10 samples are in the category of distressed companies, it turns out that from the prediction results of the Grover model there is no sample data that is correctly predicted to be in financial distress. So that as many as 10 sample data are predicted incorrectly. While the type II error of 0% reflects that as many as 23 samples in the category of non-distressed companies are correctly predicted in a non-financial distress condition by the Springate model.

4.7 Comparison of Accuracy Level and Error Rate of Financial Distress Prediction Model

The following table compares the accuracy and error rates of the financial distress prediction models of the three models:

Table 7. Comparison of Accuracy Level and Error Rate of Financial Distress Prediction Model

Ranking	Model	Accuracy Level	Type I Error	Type II Error
1	Springate	81,81%	18,18%	0%
2	Grover	69,69%	30,30%	0%
3	Zmijewski	69,69%	27,27%	3,03%

Based on table 7, it can be seen that the model that has the highest level of accuracy in this study is the Springate model with an accuracy level of 81.81% and has a type I error value of 18.18% and type II error of

0%. While the Grover model and the Zmijewski model have the same accuracy, which is 69.69% but have different error rates.

4.8. Discussions

Based on the theory that states that financial distress is a condition where the company's financial decline occurs before bankruptcy and liquidation. By predicting the occurrence of financial distress, it can prevent the bankruptcy of a company. The occurrence of financial distress can be predicted by several models. In addition, to determine the most accurate prediction model is to see the accuracy level of each model. To measure the level of accuracy is to compare the number of correct predictions with the number of samples.

In addition, the next benchmark is by looking at the error rate of each model. The error rate is divided into two, the first is Type I Error is an error that occurs when the model predicts a non-distressed sample but in reality experiences financial distress. To measure Type I Error is to compare the number of Type I errors with the number of samples. While the second error rate is Type II Error, which is an error that occurs when the model predicts the sample experiencing financial distress but in reality does not experience financial distress. To measure Type I Error is to compare the number of Type II errors with the number of samples.

Of the three prediction models used in this study, there is one common ratio used in each model. The ratio in question is the Return On Assets ratio. Although there is one ratio used in common, it produces different scores from each prediction model. In this study, when viewed based on the level of financial distress accuracy, the Springate model has the highest level of accuracy when compared to other financial distress prediction models. The Springate model has an accuracy rate of 81.81% with a type I error of 18.18%, and a type II error of 0%. This is supported by the Sales to Total Assets ratio in the Springate model formula.

The Sales to Total Assets ratio shows the level of efficiency of company management in using all assets owned to generate sales and earn profits. So it can be seen that the higher the value of the ratio of sales to total assets, the higher the income earned by the company and will avoid financial distress. Vice versa, if the ratio value is lower, the lower the level of income obtained by the company. This allows the company to experience financial distress. Based on this, the company must maintain and manage its assets optimally in order to generate maximum sales and profits in order to avoid financial distress.

V. CONCLUSION

Based on the research results, the Zmijewski model predicts that there are 2 sample data of startup companies that will experience financial distress. The Springate model predicts 4 sample data of startup companies experiencing the financial distres. While the Grover Model predicts no startup companies experiencing the financial distress. Of the three prediction models used, there is one common ratio used in each model. The ratio in question is the Return On Assets ratio. Although there is one ratio used in common, it produces different scores from each prediction model. The highest level of accuracy among the three models Zmijewski, Springate, and Grover is the Springate model with an accuracy value of 81.81% and a type I error value of 18.18% and a type II error value of 0%. This is supported by the Sales to Total Assets ratio in the Springate model formula. Sales to Total Assets ratio shows the level of efficiency company management in using all assets to generate sales and earn profits. Therefore, companies must maintain and manage their assets optimally in order to generate maximum sales and profits in order to avoid financial distress. Suggestions for future researchers are to examine other sectors and use other financial distress prediction models such as the Ohlson, Taffler, Fulmer, Foster, Zavgren, Neuro fuzzy, Internal Growth, and CA-Score models and use the latest year period.

REFERENCES

[1] Pateli, A.G. & Giaglis, G.M. (2005). *Technology innovation-induced business model change: A contingency approach, Journal of Organizational Change Management, 18(2). 167-183.*

[2] Permadi, D. (2017). Menyongsong Kewirausahaan Digital Indonesia. Yogyakarta: Gadjah Mada University Press.

[3] Ries, E. (2011). *The Lean Startup* (1 ed.). United States: Crown Business. Diambil kembali dari www.crownpublishing.com

[4] Startup Ranking. (2022). *Find the top and new startups worldwide*. (2022). StartupRanking. https://www.startupranking.com/

[5] Rizaty, M. A. (2022). *Singapura Paling Banyak Sumbang Unicorn di Asia Tenggara*. Dataindonesia.id; dataindonesia. https://dataindonesia.id/digital/detail/singapura-paling-banyak-sumbang-unicorn-di-asia-tenggara

[6] Mirawati, I. (2021). Pemanfaatan Teori Komunikasi Persuasif Pada Penelitian E-Commerce Di Era Digital. *Medium: Jurnal Ilmiah Fakultas Ilmu Komunikasi*, *9*(1), 58-80.

[7] Gompers, P., & Lerner, J. (2001). The venture capital revolution. *Journal of economic perspectives*, *15*(2), 145-168.
[8] Mulya. (2020). *Riset KIC : Perempuan Lebih Sering Belanja di E-Commerce Ketimbang Pria*. Retrieved December 28, 2022, from katadata.co.id website: https://katadata.co.id/agustiyanti/digital/5f297dd1ae890/riset-kic-perempuan-lebih-sering-belanja-di-e-commerce-ketimbang-pria
[9] Kharisma, D. B. (2021). Membangun Kerangka Pengaturan Startup Di Indonesia. *Jurnal Rechts Vinding: Media Pembinaan Hukum Nasional*, *10*(3), 431-445.
[10] Kompas. (2022). Daftar PHK Massal Startup Bertambah Panjang, Kini Ada 19 Perusahaan Sepanjang 2022 Halaman all - Kompas.com. Retrieved December 28, 2022, from KOMPAS.com
[11] Yudistira. (2022). 5 Penyebab Startup di RI Ramai-ramai Lakukan PHK. Retrieved December 28, 2022, from https://www.idxchannel.com/
[12] Fahmi, Irham. (2012). "Analisis Kinerja Keuangan" , Bandung: Alfabeta
[13] Almilia, L. S., & Kristijadi, K. (2003). Analisis rasio keuangan untuk memprediksi kondisi financial distress perusahaan manufaktur yang terdaftar di bursa efek Jakarta. *Jurnal Akuntansi dan Auditing Indonesia*, *7*(2).
[14] Ross, S., (1977). The Determinant of Financial Structure: The Incentive Signaling Approach. Bell Journal of Economics. Spring: 23-40.
[15] Scott, B. & Brigham, E. F. (2008). Essentials of Managerial Finance. United States of America: Thomson South-Western
[16] Rachmawati, L., & Nur, D. I. (2021). Analisis Rasio Keuangan Untuk Memprediksi Kondisi Financial Distress di Sektor Basic Industry and Chemical Pada Tahun 2016-2019 di Bursa Efek Indonesia. Jurnal E-Bis, 5(2), 478-488
[17] Meitasari, D. A., & Anwar, M. (2021). Analisis Nilai Perusahaan Pada Perusahaan Consumer And Goods Industry Bursa Efek Indonesia. Revitalisasi : *Jurnal Ilmu Manajemen*, *10*(1), 29-38.
[18] Spence, M. (1973). Job Market Signaling. The Quarterly Journal of Economics, Vol. 87, No. 3., pp. 355-374.
[19] Scott, B. & Brigham, E. F. (2008). Essentials of Managerial Finance. United States of America: Thomson South-Western
[20] Jensen, M. C. & Meckling, W. H. (1976). *Theory Of The Firm: Managerial Behvior, Agency Cost, and Ownership Structure*, Journal of Financial Economics, Vol. 76, pp. 305-360.
[21] Yuniningsih, Y. (2017). Seberapa Besar Kepemilikan Saham Berperan Dalam Penentuan Nilai Perusahaan Dengan Tinjauan Agency Theory. *Jurnal Darussalam: Jurnal Pendidikan, Komunikasi dan Pemikiran Hukum Islam*, *9*(1), 112-121.
[22] Tandiontong, M. (2016). *Kualitas Audit Dan Pengukurannya.* Alfabeta: Bandung
[23] Kasmir. (2018). *Analisis Laporan Keuangan.* Depok: PT Raja Grafindo Persada.
[24] Platt, H. D. & Platt, M. B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias.*Journal of Economics and Finance.*
[25] Wruck, K. H. (1990). Financial Distress, Reorganization, and Organizational Efficiency. *Journal of Financial Economics.* 27, 419-444.
[26] Almilia, L. S., & Kristijadi, K. (2003). Analisis rasio keuangan untuk memprediksi kondisi financial distress perusahaan manufaktur yang terdaftar di bursa efek Jakarta. *Jurnal Akuntansi dan Auditing Indonesia*, *7*(2).
[27] Zmijewski, M. (1983). Predicting Corporate Bankruptcy: An Empirical Comparison of the Extant Financial Distress Models. Working paper. SUNY at Buffalo.
[28] Kasmir. (2009). Analisis Laporan Keuangan. Jakarta; Rajawali Pres.
[29] Susilo, N. U., & Suwaidi, R. A. (2022). Pengaruh Rasio Keuangan Dalam Memprediksi Financial Distress Pada Perusahaan Sektor Pertanian Yang Terdaftar di Bursa Efek Indonesia. *Nusantara: Jurnal Ilmu Pengetahuan Sosial*, *9*(1), 106-114
[30] Arohmawati, P. P., & Pertiwi, T. K. (2021). Predicting of Financial Distress with the Alatman Z-Score Model of Retail Companies Listed on IDX. *Jurnal Ekonomi*, 273-280.
[31] Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. Journal of Acoounting Research. 22, 59-82.
[32] Permana, R. K., dkk (2017). Prediksi Financial Distress pada Perusahaan Manufaktur di Bursa Efek Indonesia. *Esensi: Jurnal Bisnis dan Manajemen*, *7*(2), 149-166.
[33] Springate, G. L.V. (1978). Predicting the Possibility of Failure in a Canadian Firm. M.B.A. Research Project, Simon Fraser University. January.

[34] Riana, D. & Diyani, L. A. (2016). Pengaruh Rasio Keuangan dalam Memprediksi Perubahan Laba pada Industri Farmasi (Studi Kasus pada BEI Tahun 2011- 2014). Jurnal Online Insan Akuntan, Vol. 1, No. 1, Juni 2016.
[35] Kasmir. (2009). Analisis Laporan Keuangan. Jakarta; Rajawali Pres.
[36] Hanafi, M. & Halim, A. (2005). Analisis Laporan Keuangan Edisi Kedua. Yogyakarta: UPP AMP YKPN.
[37] Springate, G. L.V. (1978). Predicting the Possibility of Failure in a Canadian Firm. M.B.A. Research Project, Simon Fraser University. January.
[38] Grover, Jeffrey. (2001). "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy : A Service Industry Extension of Altman's Z-Score Model of Bankruptcy Prediction". Nova Southeastern University.
[39] Riana, D. & Diyani, L. A. (2016). Pengaruh Rasio Keuangan dalam Memprediksi Perubahan Laba pada Industri Farmasi (Studi Kasus pada BEI Tahun 2011- 2014). Jurnal Online Insan Akuntan, Vol. 1, No. 1, Juni 2016.
[40] Kasmir. (2009). Analisis Laporan Keuangan. Jakarta; Rajawali Pres.
[41] Altman, E. I. (2000). Predicting Financial Distress of Companies: Revisiting The Z-Score and ZETA Models. New York: Stem School of Business, New York University.

Appendix

Table of Financial Distress Prediction Calculation Results

No	Company Code	Year	Zmijewski	Category	Springate	Category	Grover	Category
1	CASH	2019	-0,933717613	*NFD*	0,471353724	*FD*	1,7690834	*NFD*
		2020	-1,651858574	*NFD*	0,896455636	*NFD*	1,5344392	*NFD*
		2021	-2,207606988	*NFD*	1,395882663	*NFD*	1,987386	*NFD*
2	DIVA	2019	-3,309468713	*NFD*	2,656805121	*NFD*	1,6270447	*NFD*
		2020	-3,187767407	*NFD*	2,47676243	*NFD*	1,5797278	*NFD*
		2021	-6,157292945	*NFD*	3,811055948	*NFD*	1,7192986	*NFD*
3	DMMX	2019	-4,065293629	*NFD*	1,737280424	*NFD*	1,7582644	*NFD*
		2020	-3,614328653	*NFD*	1,810173529	*NFD*	1,6725088	*NFD*
		2021	-4,548649938	*NFD*	2,485000782	*NFD*	1,7110711	*NFD*
4	GLVA	2019	0,214357378	*FD*	1,414624057	*NFD*	1,1323969	*NFD*
		2020	-1,297568739	*NFD*	2,802230181	*NFD*	2,2735866	*NFD*
		2021	-0,996784585	*NFD*	2,042997431	*NFD*	1,7379067	*NFD*
5	HDIT	2019	-4,175730271	*NFD*	13,62222312	*NFD*	1,9185383	*NFD*
		2020	-3,586950084	*NFD*	4,251191586	*NFD*	1,6610238	*NFD*
		2021	-2,723809452	*NFD*	4,699926167	*NFD*	1,4272406	*NFD*
6	KIOS	2019	-0,67426936	*NFD*	4,74019096	*NFD*	1,2544424	*NFD*
		2020	0,949342745	*FD*	1,906367882	*NFD*	0,621087	*NFD*
		2021	-3,161240243	*NFD*	3,187868183	*NFD*	2,0001287	*NFD*
7	LUCK	2019	-2,845771545	*NFD*	1,603914354	*NFD*	1,8183551	*NFD*
		2020	-3,163699008	*NFD*	1,774504048	*NFD*	1,8820862	*NFD*
		2021	-3,263308287	*NFD*	1,860195346	*NFD*	1,9116245	*NFD*
8	MCAS	2019	-3,322682612	*NFD*	3,371788481	*NFD*	1,7159778	*NFD*
		2020	-2,900630338	*NFD*	3,699381619	*NFD*	1,6666721	*NFD*
		2021	-2,937258278	*NFD*	3,575381705	*NFD*	1,5824309	*NFD*
9	NFCX	2019	-3,267849341	*NFD*	3,03323843	*NFD*	1,634405	*NFD*
		2020	-2,797850074	*NFD*	3,215483363	*NFD*	1,4765033	*NFD*
		2021	-3,481695683	*NFD*	3,29007564	*NFD*	1,4553406	*NFD*
10	PGJO	2019	-0,75809267	*NFD*	-0,822432139	*FD*	1,4004972	*NFD*
		2020	-1,052216322	*NFD*	-0,990420591	*FD*	1,6670579	*NFD*
		2021	-1,841201205	*NFD*	0,063988789	*FD*	1,7063065	*NFD*
11	TFAS	2019	-2,721345847	*NFD*	2,553977202	*NFD*	1,9607801	*NFD*
		2020	-2,737447061	*NFD*	2,304649023	*NFD*	1,8969327	*NFD*
		2021	-3,086867265	*NFD*	2,344595536	*NFD*	1,7628838	*NFD*

Description :
NFD = Non Financial Distress
FD = Financial Distress