Jurnal Muara Ilmu Ekonomi dan Bisnis
Vol. 7, No. 2, Oktober 2023 : hlm 311-326

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

EARNINGS MANAGEMENT AND PROBABILITY OF DEFAULT ANALYSIS OF NON-FINANCIAL COMPANIES IN INDONESIA DURING THE COVID-19 PANDEMIC

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Masuk : 10-06-2023, revisi: 27-08-2023, diterima untuk diterbitkan : 04-09-2023

ABSTRAK

Pada masa pandemi COVID-19, ekonomi Indonesia mengalami pertumbuhan negatif 2,19 persen (2020). Kondisi ini mempengaruhi penurunan bisnis di Indonesia yang berdampak pada peningkatan *Non Performing Loan* perbankan. Umumnya, penilaian kredit oleh perbankan dilakukan menggunakan informasi yang terdapat pada laporan keuangan sehingga pencatatan akuntansi yang benar dapat mempengaruhi kualitas kredit. Penelitian ini bertujuan untuk mempelajari apakah manajemen laba (*earnings management*) yang dilakukan oleh perusahaan selama krisis pandemi COVID-19 memiliki pengaruh signifikan terhadap kemungkinan gagal bayar (*probability of default*), khususnya bagi perusahaan sektor non keuangan di Indonesia. Data penelitian diperoleh dari Bursa Efek Indonesia periode 2019 – 2021 dimana *probability of default* dihitung dengan menggunakan *KMV-Merton Model* dan *earnings management* menggunakan metode *F-score Dechow*. Hasil penelitian menunjukkan bahwa terdapat peningkatan jumlah perusahaan yang memiliki *probabilitas default* pada masa pandemi COVID-19, namun jumlah perusahaan yang terindikasi melakukan *earnings management* mengalami penurunan. Hasil uji menunjukan bahwa pengaruh *earnings management* terhadap *probability of default* tidak signifikan. Namun demikian, pihak yang berkepentingan harus dapat sedini mungkin mengidentifikasi adanya manajemen laba yang dapat berdampak buruk terhadap kualitas kredit dan mengantisipasi kemungkinan gagal bayar di kemudian hari.

Kata Kunci: manajemen laba, probabilitas *default*, risiko kredit, *KMV-Merton Model, F-Score Dechow*

ABSTRACT

During the COVID-19 pandemic, the Indonesian economy experienced negative growth of 2.19 percent (2020). This condition affects the decline in business in Indonesia, which impacts the increase in bank Non-Performing Loans. Generally, credit assessment by banks is performed based on the information figured in financial statements and therefore the accounting records can affect credit quality. This research aims to study whether earnings management carried out by companies during the COVID-19 pandemic crisis has a significant effect on the probability of default, especially for non-financial sector companies in Indonesia. The data was obtained from the Indonesia Stock Exchange for the period 2019 – 2021. The probability of default was calculated using the KMV-Merton Model and earnings management using the F-score Dechow method. The results showed that there was an increase in the number of companies that had a probability of default during the COVID-19 pandemic, but but the number of companies that indicated earnings management decreased. The result showed that the effect of earnings management on the probability of default is not significant. However, interested parties must be able to identify earnings management as early as possible, which can have an adverse impact on credit quality and anticipate possible defaults in the future.

Keywords: *earnings management, probability of default, credit risk, KMV-Merton Model, F-Score Dechow.*

1. INTRODUCTION

The outbreak of the COVID-19 virus that first occurred in Wuhan, China in 2019 not only affected the health of global citizens but also the economy. Wu, Zhan, Xu & Ma (2023) said that China, which was the first country to be hit by the COVID-19 pandemic, carried out a strict lockdown with the aim of restraining the spread of the virus throughout the world and this had a negative impact on the Chinese economy where the average growth fell to 2.3% in 2020. The Indonesian government also imposed a lockdown policy that disrupted people's mobility between cities and countries. This lockdown caused the Indonesian economy to contract and experience negative growth of 2.19% in 2020 compared to conditions in 2019 (Otoritas Jasa Keuangan, 2021).

The economic downturn that occurred had an impact on all lines of industry, including the banking industry. Otoritas Jasa Keuangan (2021) noted a decrease in expansion plans and capital expenditures, which was reflected in a decrease in the use of bank loans in 2020. In addition, along with the weakening of corporate performance, the level of Non-Performing Loans in banking institutions has increased significantly, especially in the mining sector. Based on statistical data from Otoritas Jasa Keuangan (2021), the increase in the banking Non-Performing Loan ratio to 3% occurred in May 2020 where previously it was only 2.57% at the end of 2019 while bank lending decreased from IDR 5,633 billion at the end of 2019 to IDR 5,481 billion at the end of 2020. Otoritas Jasa Keuangan (2021) noted that at the time of the pandemic, almost 44% of non-financial corporations in Indonesia recorded an Interest Coverage Ratio (ICR) below 1, which means that almost all of the profits earned by corporations in Indonesia were used to pay bank interest expenses. Under these conditions, if the company is unable to record profits, the company will not be able to pay its interest payment obligations, which in turn can lead to non-performing loans.

In deciding to grant credit facilities to prospective debtors, credit assessment conducted by banks on company's financial statements is one of the important things because the presentation of accounting figures reported in the financial statements affects the calculation of the company's financial ratios and the feasibility of granting credit. However, there are times when in order to get a good assessment, the management of a prospective debtor company manipulates the presentation of financial statements which is often referred to as earnings management (Sulistyanto, 2008). Earnings management activities carried out by prospective debtors can affect the assessment of banks who want to know the real performance of the company because the accounting figures reported in the financial statements are so good that they affect the feasibility of granting credit by banks. Thus, this earnings management can trigger a high ratio of non-performing loans and the possibility of default, especially when the financial crisis hits the world again (Naili & Lahrichi, 2022).

The earnings management case that has become an important lesson in Indonesia is the case that occurred at PT Garuda Indonesia Tbk. In the 2018 Financial Statements, the company recorded unearned income (still receivable) so that the company's profits looked higher but in fact the company suffered losses (Sugianto, 2019). Mobility restrictions that occurred in 2020 due to the spread of COVID-19 also had a significant impact on PT Garuda Indonesia Tbk, where the company could not operate properly so that this affected the company's revenue and the company had to restructure to pay most of its obligations (Resia, 2021).

Research on the relationship between earnings management and bankruptcy risk has previously been conducted in Indonesia by Agustia et al. (2020) on 1.068 non-financial companies listed on the Indonesia Stock Exchange (IDX) from 2014 - 2016 using the Modified Jones Model to calculate Discretionary Accruals (DA) as a proxy for earnings management and Altman Z-Score as a model for calculating bankruptcy risk. Agustia et al. (2020) noted that there is no relationship between earnings management and bankruptcy risk, while companies that implement one of the two generic business strategies, namely cost leadership or differentiation, can reduce bankruptcy risk. The results of this study differ from the results conducted by researchers in other countries including Li et al. (2020) and Veganzones et al. (2023) so that through this study, researchers will

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

analyse whether the difference in time horizon and the difference in proxies for calculating earnings management and default probability with the research of Agustia et al. (2020) will have different results.

To identify indications of earnings management, researchers will use the Dechow F-score method used by (Dechow et al., 2011)to test companies that commit fraud in America. The F-score value is considered a warning or indicator of possible misstatements in the financial statements. This method was used by Aghghaleh et al. (2016) where in their research they compared the Beneish M-score in terms of sensitivity in predicting fraud cases in companies in Malaysia and found that the Dechow F-score outperformed this model by 73.17% compared to 69.51%. Other research using this formula was conducted by Ratmono et al. (2020) and (Hugo, 2019).

In calculating the probability of default, researchers will use the Merton model developed by Crosbie & Bohn (2003) through Moody's KMV Corporation as a proxy to identify default risk. Wibowo (2017) in his research said that banks can use the Merton Model compared to Altman's Z score and the Ohlson Model because the Merton Model is widely recognised as a model that has a strong theoretical basis even though it has its own problems in its implementation because the variables it uses are unobservable. Some other researchers who use the KMV-Merton Model as the basis for calculating the probability of default include Bharath et al. (2004), (Chen & Chu, 2014), (Canh & Khoa, 2014), (Malasari et al., 2020) and (Yusof et al., 2021).

By using these two methods, it is hoped that this research can be more reliable in calculating indications of earnings management and probability of default in Indonesia during the COVID-19 pandemic so that it can contribute to interested parties including banks, investors and regulators to understand earnings management activities and the potential for an increase in default probability during the crisis in Indonesia. Thus, the parties can apply the precautionary principle in assessing the company's financial statements to anticipate any indications of earnings management activities that have the possibility of affecting the increase in the probability of default during the crisis.

Problem Formulation

To see indications of earnings management and the probability of default in Indonesia during the COVID-19 pandemic, the problems analysed in this study are (1) Is there a significant difference in the number of companies that fall into the default category during the period before the COVID-19 pandemic (2019) and during the COVID-19 pandemic (2020 - 2021), (2) Which industry sector has the highest probability of default during the COVID-19 pandemic and which industry sector has the most indications of earnings management activities? (3) Does accrued earnings management activity have a significant effect on the probability of default during the COVID-19 pandemic?

Literature Review

Credit Risk

Credit risk is the possibility of losing money due to a counterparty's inability, unwillingness, or untimeliness to fulfil financial obligations. Whenever there is a possibility that a counterparty will not pay an amount owed, fulfil a financial commitment, or honour a claim, there is credit risk (Bouteille & Coogan-Pushner, 2015). Mehmood & De Luca (2023) noted that banks are exposed to credit risk if the borrower is unable to repay the loan amount in a timely manner, thus increasing the bank's credit risk as explained by van Greuning & Bratanovic (2020).

Hunjra et al. (2022) in their research on 76 commercial banks from 4 countries namely Pakistan, India, Bangladesh, and Sri Lanka for the period 2009-2018, said banks experience credit risk if the creditworthiness of debtors is not evaluated effectively. According to Mehmood & De Luca (2023) if both cases occur at the same time it will result in the accumulation of non-performing accounts thus affecting the viability and stability of the bank.

Probability of Default

Probability of Default (PD) is the likelihood that an obligor will default over a certain period of time (Bouteille & Coogan-Pushner, 2015). To determine the probability of default, Bouteille & Coogan-Pushner (2015) suggest analysing the obligor's financial strength and using historical data by observing the default frequency of obligors or companies with similar ratings. In addition, there are several methods that can be used to measure the probability of obligor default, including Z-Score, ZETA, RiskCalc, CreditModel, Credit Risk Tracker and BondScore models that are applied to different situations depending on credit policy, credit review, lending, validation and securitisation.

Along with the report submitted by the Otoritas Jasa Keuangan (2021), several studies in other countries state that there is an increase in Non-Performing Loans as a result of the COVID-19 pandemic, including in China (Kryzanowski et al., 2022) as well as Pakistan, India, Bangladesh and Sri Lanka (Hunjra et al., 2022). Quoting the explanation of Kryzanowski et al. (2022) the average non-performing loan ratio (NPL) of Chinese commercial banks at the end of the second quarter of 2020 was 1.94%, the highest since 2009.

In Indonesia itself, with government regulations related to mobility restrictions, some companies are experiencing difficulties operating, which has an impact on reducing company income, so the potential for default during a pandemic is quite high. Therefore, Otoritas Jasa Keuangan (2020) issued regulation No. 11 /POJK.03/2020 concerning National Economic Stimulus as a Countercyclical Policy on the Impact of the Spread of Coronavirus Disease 2019, policies that related to restructuring and relaxation of payments which aim to reduce the potential for defaults that can have an impact on banking stability in Indonesia.

Moody’s KMV-Merton Model

The KMV-Merton Model is essentially the same as the Moody's KMV-Merton Model. This change in designation occurred because in 2002 KMV was acquired by Moody's, resulting in a name change to Moody's - KMV. Crosbie & Bohn (2003) are researchers who developed and explained the application of the Moody's KMV-Merton Model in calculating default risk. Crosbie & Bohn (2003) said there are three main elements that can determine the probability of a company's default, namely asset value, asset risk and leverage where the company's default risk increases when the value of assets approaches the value of liabilities and the company will default when the market value of assets is not sufficient to pay liabilities. Therefore it is very important to be able to calculate the default point, which is the point where the value of the company's assets will default, which generally lies between total liabilities and short-term liabilities.

The variables calculated in KMV Merton's formula are as follows (Crosbie & Bohn, 2003):

1. Market value of equity. It calculated by multiplying share price and shares outstanding.
2. Book liabilities. The value taken from company balance sheet.
3. Market value of assets. The value calculated using option-pricing model.
4. Asset volatility. The value calculated using option-pricing model.
5. Point Default. It calculated from liabilities payable in 1 year.

https://doi.org/10.24912/jmieb.v7i2.24131

 ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

6. Distance to Default. It's calculated using this formula: $\frac{(\text{market value of assets} - \text{default point})}{(\text{market value of assets})\ (\text{asset volatility})}$

Tudela & Young (2003) in their research tested the PD score using 5 thresholds, namely 5%, 10%, 15%, 20% and 30%. However, Tudela & Young (2003) said that with the smallest threshold of 5%, they could not predict failure if the company had a PD score below 5%, especially for measuring the average PD score in 1 year. Therefore, this study uses a PD threshold of 1% in order to be more sensitive in measuring the probability of default due to the short research period. In addition, the research was conducted under the influence of the COVID-19 pandemic.

Earnings Management

The efforts of company managers to intervene in the information contained in the financial statements so as to provide misleading information for stakeholders who want to know the real performance of the company are often called earnings management. This definition is in accordance with Healy & Wahlen (1998) that earnings management occurs when managers use judgements in financial statements and in structuring transactions to alter financial statements to mislead some stakeholders about the company's economic performance or to influence contractual outcomes that depend on reported accounting numbers. However, not all researchers argue that earnings management is negative and misleading. Jiraporn et al. (2008) in their research stated that earnings management may benefit the company if it is done to increase the value of information contained in earnings for the benefit of the company.

In their research, Dechow et al. (2011) analysed the financial characteristics of companies that perform earnings management and created 3 calculation models to predict the activity where the 3 models each use slightly different analysis data. In Model 1, the variables analysed come from the main financial statements which include company performance and accrual quality. The variables measured in Model 2 include non-financial and off-balance sheet measures such as operational leases. Meanwhile, Model 3 adds variables related to prior stock price performance and book-to-market ratio. The analysis result of these three models is a logistic probability scale (F-Score) that is used as a signal to indicate the possibility of earnings management.

There are several variables calculated in Model 1 as follows:

Table 1. Dechow's F-Score Variables
Source: Dechow et al. (2011)

Variable	Formula
RSST accruals	RSST accruals = $\frac{(\Delta WC + \Delta NCO + \Delta FIN)}{\text{Average total assets}}$ Where: • ΔWC = [current assets – cash and short-term investments] – [current liabilities – debt in current liabilities] • ΔNCO = [total assets – current assets - investments and advances] – [total liabilities – current liabilities – long-term debt] • ΔFIN = [short-term investments + long-term investments] – [long-term debt + debt in current liabilities + preferred stock]
Change in receivables (ΔREC)	$\Delta REC = \frac{\Delta\text{Accounts receivables}}{\text{Average total assets}}$
Change in inventory (ΔINV)	$\Delta INV = \frac{\Delta\text{Inventory}}{\text{Average total assets}}$
Change in cash sales (ΔCASHSALES)	$\Delta CASHSALES = \frac{\text{Sales}}{\Delta\text{Account Receivables}}$
Change in earnings (ΔROA)	$\Delta ROA = \left[\frac{Earnings\ t}{Average\ total\ assets\ t}\right] - \left[\frac{Earnings\ t{-}1}{Average\ total\ assets\ t{-}1}\right]$

https://doi.org/10.24912/jmieb.v7i2.24131

Variable	Formula
Actual issuance (Issue)	A dummy variable where the value of 1 is given if there is an issuance of new securities (stocks and bonds) and the value of 0 if there is no issuance of new securities (stocks and bonds).

In calculating the F-score, the calculation steps taken by Aghghaleh et al. (2016) and (Hugo, 2019) are as follows:

- Calculate the predicted value with the following formula:
  Value = -7,893 + 0,790*RSST + 2,518*ΔREC + 1,191*ΔINV + 1,979*SOFTASSETS + 0,171*ΔCASHSALES – 0,932*ΔROA + 1,029*ISSUE
- Predicted value is converted to probability with the following formula:
  $$\text{Probability} = \frac{e^{(Predicted\ value)}}{(1+ e^{(Predicted\ value)})}$$
  Where: e= 2,71828183
- After getting the probability, the calculation is carried out to get the F-score as follows:
  $$\text{F-score} = \frac{\text{Probability}}{\text{Unconditional probability}}$$
  Where: Unconditional probability = 0,00345

The F-score results obtained will be interpreted as follows:

- More than 2,125 → High Risk
- More than 1,593 → Substantial Risk
- More than 1 → Above Normal Risk
- Less than or equal to 1 → Normal or Low Risk

If the F-Score shows a number less than 1 (< 1), it means that there is no financial statement manipulation. If the F-Score is more than 1 (> 1), it can signal an indication of fraud in the company's financial statements. An F-Score value equal to 1 indicates that the company has an equal probability of error between the predicted probability and the unconditional probability (the probability of an event occurring with a certain outcome regardless of other conditions). An F-Score greater than 1 indicates a higher probability of misstatement because the estimated probability is higher than the unconditional probability. This can also indicate that the company's financial statements have been altered by the company (Ratmono, Darsono, & Cahyonowati, 2020). The interpretation of F-Score shows that the higher the F-Score, the higher the risk of corporate fraud in conducting earnings management.

2. RESEARCH METHOD

The research was conducted on non-financial companies listed on the Indonesia Stock Exchange for the period 2019 to 2021 using descriptive quantitative research methods. Researchers will also analyse industries that have indications of earnings management and the highest probability of default during the test period. To test the effect of accrued earnings management activity on the probability of default during the COVID-19 pandemic, researchers will conduct panel data regression on F-score and PD score.

The research data comes from secondary data obtained from financial reports or annual reports published by the Indonesia Stock Exchange for the period 2018 to 2021. Secondary data is obtained from the official website of the Indonesia Stock Exchange, namely https://www.idx.co.id/. Other data are data contained in journals and previous research results, Bloomberg and data from the Otoritas Jasa Keuangan, Biro Pusat Statistik and Bank Indonesia.

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

The research population is companies listed on the Indonesia Stock Exchange for the period 2019 to 2021 where as of 27 February 2023 there are 845 companies listed on the stock exchange. From the company data, companies will be excluded from the analysis of companies with the following criteria (1) Companies engaged in finance such as banking and multifinance, (2) Companies that have been delisted in 2022, (3) Companies that have less than 5 years of listing, (4) Companies that have been suspended in 2023 and (5) Having anomalous data so that the calculation of the probability of default cannot be done, including not recording short term and long term borrowing in the financial statements and no stock price movements for the last 3 years.

From the results of data selection, the research sample was obtained as many as 374 companies with a total observation data of 1.496 company financial reports from 2018 to 2021. The 2018 financial statement data is needed to calculate changes in several items in the financial statements as the basis for calculating earnings management. The 374 sample data companies will calculate the probability of default using the KMV-Merton Model (PD score) method and earnings management using the Dechow F-score method to see companies that have indications of earnings management activities.

The research will be conducted using the following framework:

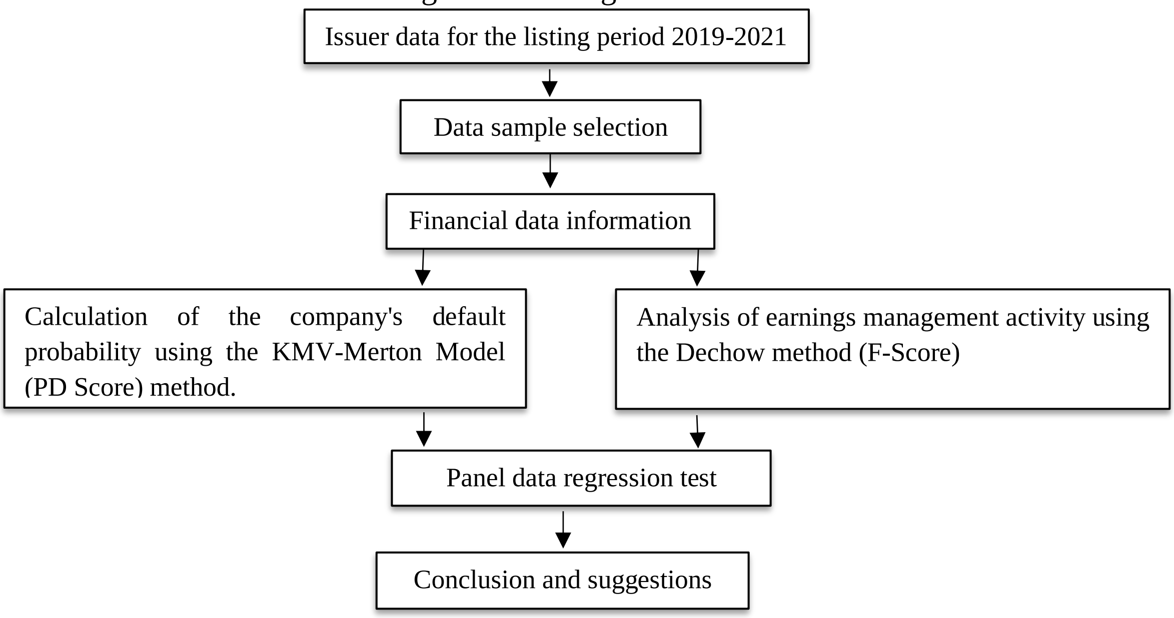

Figure 1. Research Framework

Descriptive Statistics

Descriptive statistical analysis is carried out to see an overview of the data from the calculation of the probability of default to answer the first research question, which is to see the difference in the number of companies in the default category during the period before the COVID-19 pandemic (2019) and during the COVID-19 pandemic (2020-2021) so that it can be seen whether during the pandemic there was an increase in the number of companies in the default category. In addition, descriptive statistical analysis is also carried out on the results of the F-Score calculation as an indication of companies that carry out earnings management in the period before the COVID-19 pandemic (2019) and during the COVID-19 pandemic (2020-2021). It also used to see industry sectors that are indicated to have a risk of doing earnings management and have the highest probability of default during a pandemic.

Research Hypothesis

https://doi.org/10.24912/jmieb.v7i2.24131

To see whether accrued earnings management activities have a significant effect on the probability of default during the COVID-19 pandemic, especially in non-financial companies listed on the IDX, researchers developed the following hypothesis:

H0 : Accrued earnings management activities do not have a significant effect on the probability of default during the COVID-19 pandemic.

Ha : Accrued earnings management activities have a significant influence on the probability of default during the COVID-19 pandemic.

Panel Data Regression Test

To answer the problem formulation number 3 which is does accrued earnings management activity have a significant effect on the probability of default during the COVID-19 pandemic, researchers will conduct panel data regression on these two variables:

Table 2. Research Variables
Source: Results of Researcher Data Processing, 2023

	Variable	**Scale**
Independent Variable (X)	Earnings management (F-Score)	Ratio
Dependent Variable (Y)	Probability of default (PD score)	Ratio

It performs using the stages of model determination to interpretation as explained by Gujarati (2003). The stages are (1) Determination of the estimation model that use 3 ways i.e. Common Effect Model or Pooled Least Square (PLS), Fixed Effect Model (FE) or Random Effect Model (RE); (2) Determination of estimation method that use 3 test i.e. Chow Test, Hausman Test and Lagrange Multiplier Test; (3) Assumption testing and model fit using the test of normality, multicollinearity, heteroskedasticity and autocorrelation; (4) Interpretation that use adjusted R-Square, F Test, Partial T Test, Goodness of Fit and Regression Equation.

3. RESULTS AND DISCUSSION

Probability of Default

Based on calculations using the KMV-Merton Model, the statistical results of the probability of default are obtained as follows:

Table 3. Descriptive Statistics of Probability of Default
Source: Results of Researcher Data Processing, 2023

	2019	**2020**	**2021**
Mean	3,379%	5,817%	7,208%
Standard Error	0,715%	0,946%	1,071%
Standard Deviation	13,824%	18,304%	20,710%
Sample Variance	1,911%	3,350%	4,289%
Kurtosis	28,880	13,429	10,078
Skewness	5,182	3,657	3,248
Range	100%	100%	100%
Minimum	0%	0%	0%
Maximum	100%	100%	100%
Confidence Level (95%)	0,014056	0,01861	0,02106

In 2019, the average default probability value was 3.379% with a minimum value of 0% and a maximum value of 100%. This average value has increased in 2020 and 2021 to 5.817% and 7.208%. With an increase in the percentage of this value, there is an increase in the potential probability of default in 2020 and 2021 which is in line with the results of research by the (Otoritas Jasa Keuangan, 2021) that corporate NPLs tend to increase in 2020.

Jurnal Muara Ilmu Ekonomi dan Bisnis
Vol. 7, No. 2, Oktober 2023 : hlm 311-326 ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

By using a threshold of 1%, the value contained in the descriptive statistics is in line with the increase in the number of companies that have a probability of default in 2020 and 2021 as follows:

Table 4. Data Probability of Default of Non-Financial Company 2019 - 2021
Source: Results of Researcher Data Processing, 2023

	2019	**2020**	**2021**
Company with PD < 1%	332	319	309
Company with PD ≥ 1%	42	55	65
% PD of sampling	11%	15%	17%

Figure 2 shows an increase in the number of companies that have a probability of default from all industrial sectors during the study period where the highest increase occurred in 2021. This increase was partly influenced by the conditions of the COVID-19 pandemic which caused a decline in corporate performance (Otoritas Jasa Keuangan, 2021).

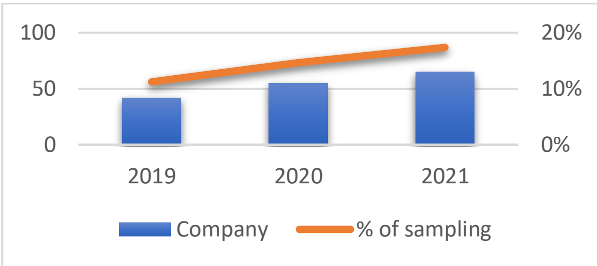

Figure 2. Probability of Default of Non Financial Company Chart 2019 - 2021
Source: Results of Researcher Data Processing, 2023

Significant increases occurred in the properties & real estate, basic materials, consumer cyclicals, consumer non-cyclicals and industrials sectors. Meanwhile, companies engaged in the technology industry sector experienced a decline because during the COVID-19 pandemic this sector became one of the communication supports when large-scale social restrictions were imposed by the government.

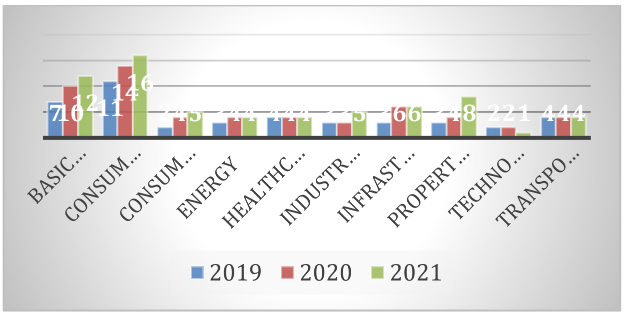

Figure 3. Graph of Default Probability by Industry Sector 2019 - 2021
Source: Researcher's Data Processing Results, 2023

In 2019, there were 4 companies that had a default probability above 90% where these companies were also indicated to carry out earnings management (above normal) namely PT MNC Studios International Tbk (consumer cyclicals), PT Pelangi Indah Canindo Tbk (basic materials), PT Ristia Bintang Mahkotasejati Tbk (properties & real estate) and PT Temas Tbk (transportation & logistic).

In 2020, there was an increase to 6 companies that had a probability of default above 90%, where several companies that had PDs above 90% in 2019 were again recorded as having high PDs in 2020. These companies are PT MNC Studios International Tbk (consumer cyclicals), PT Pelangi Indah Canindo Tbk (basic materials), PT Ristia Bintang Mahkotasejati Tbk (properties & real estate), PT Temas Tbk (transportation & logistic), PT Arthavest Tbk (consumer cyclicals) and PT Wilton Makmur Indonesia Tbk (basic materials).

In 2021, the increase occurred in the basic materials, energy and consumer non-cyclicals sectors. This is in line with the explanation of the (Otoritas Jasa Keuangan, 2021) that although coal, nickel, and CPO prices have returned to above pre-pandemic levels, overall commodity prices are still below the previous year's level. Therefore, this is quite influential on the basic materials, energy and consumer non cyclicals sectors. These companies are PT MNC Studios International Tbk (consumer cyclicals), PT Pelangi Indah Canindo Tbk (basic materials), PT Ristia Bintang Mahkotasejati Tbk (properties & real estate), PT Temas Tbk (transportation & logistic), PT Arthavest Tbk (consumer cyclicals), PT Wilton Makmur Indonesia Tbk (basic materials), PT Jakarta Kyoei Steel Works Tbk (basic materials), PT Mitra Investindo Tbk (energy), PT Bakrie Sumatera Plantations Tbk (consumer non-cyclicals).

Earnings Management

The interpretation results show that there is a decrease in the number of companies that carry out earnings management during the COVID-19 pandemic crisis. Otoritas Jasa Keuangan (2021) states that the COVID-19 pandemic has caused pressure that affects the business climate so that the net income and profits of issuers have decreased, this condition is considered to affect the tendency of companies to carry out earnings management. Because one of the components taken into account in F-Score is the change in the value of cash sales and income, so if the value of cash sales or income decreases, this can affect the company's F-Score value.

Table 5. Results of F-score Interpretation of Non-Financial Companies in 2019-2021
Source: Results of Researcher Data Processing, 2023

F-Score	Interpretation	2019	2020	2021
More than 2,125	High Risk	28 company	23 company	20 company
More than 1,593	Substantial Risk	31 company	27 company	27 company
More than 1	Above Normal Risk	174 company	173 company	146 company
Less than or equal to 1	Normal or Low Risk	141 company	151 company	181 company

Based on the results of the F-Score calculation, it can be seen that the entire industry has a risk in conducting earnings management with classifications ranging from above normal risk to high risk where the number of companies indicated to have the highest point in 2019 is 233 issuers or 62.3% of the sample. This condition has decreased to 223 issuers (59.62% of the sample) in 2020 and 193 issuers (51.6% of the sample) in 2021.

From table 6, it can be seen that the 3 sectors that have indications of the risk of doing earnings management with the highest number come from the consumer cyclicals, basic materials and Properties & Real Estate industry sectors where when compared to the previous default probability results, these three industry sectors are also in the highest position for industries that fall into the default category during the COVID-19 pandemic.

https://doi.org/10.24912/jmieb.v7i2.24131

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

Table 6. Number of Companies with Indications of Earnings Management by Industry Sector in 2019 – 2021
Source: Results of Researcher Data Processing, 2023

	2019	2020	2021
Basic Materials	41	34	31
Consumer Cyclicals	45	48	38
Consumer Non-Cyclicals	32	31	31
Energy	13	15	12
Healthcare	10	6	3
Industrials	24	19	19
Infrastructures	18	22	16
Properties & Real Estate	40	37	35
Technology	2	2	2
Transportation & Logistic	8	9	6
Total	233	223	193

Dechow et al., (2011) explain that the higher the F-Score, the higher the risk of the company committing fraud against recording revenue and profit where this can be seen from the analysis conducted on Enron. The company that applies mark-to-market accounting practices has an F-Score of 1.8 which indicates that the risk of manipulation of financial statements by Enron falls into the high risk category so that earnings management carried out by the company is considered as one of the causes of Enron's bankruptcy.

The results of descriptive statistics of earnings management conducted on all F-Score results of the research sample are as follows:

Tabel 7. Descriptive Statistics Analysis of Earnings Management of Non-Financial Companies in 2019 – 2021
Source: Results of Researcher Data Processing, 2023

Statistik	2019	2020	2021
Mean	2,7964	2,4630	1,5278
Standard Error	1,1364	0,6987	0,0544
Standard Deviation	17,3464	10,4335	0,6951
Sample Variance	300,8991	108,8570	0,4832
Kurtosis	230,0594	173,5769	10,2946
Skewness	15,1235	12,7518	2,9931
Minimum	1,0030	1,0032	1,0097
Maximum	265,6166	147,9244	5,1702
Count	233	223	163
Confidence Level (95,0%)	2,239	1,3769	0,1075

The results of the average value (mean) of statistics in 2019 and 2020 are in the high risk category where this does not reflect the real data because of the anomalous values of several companies that have numbers far above the average as follows:

Table 8. Companies with Anomalies F-Score Values in 2019 - 2021
Source: Results of Researcher Data Processing, 2023

2019		2020	
Company	***F-Score***	**Company**	***F-Score***
Wahana Pronatural Tbk	14,733	Tiphone Mobile Indonesia Tbk	29,239

2019		**2020**	
Company	***F-Score***	**Company**	***F-Score***
Perdana Karya Perkasa Tbk	12,988	Mitra Investindo Tbk	47,223
Express Transindo Utama Tbk	265,617	Kioson Komersial Indonesia Tbk	147,924

Panel Data Regression Test

The panel data regression test is conducted on all observation data where variable X is the independent variable, namely the F-score number that indicates the existence of earnings management and variable Y is the dependent variable, namely the percentage of default probability. All observation data is processed using eviews 12 software to get the right model and test.

Determination of the Estimation Model

The first step before determining the estimation method is to determine the estimation model. Researchers conducted data processing for the Common Effect (CE) and Fixed Effect (FE) estimation models. If the P-Value result is reject H0 then the best choice is FE, and vice versa if the P-Value is the P-Value accepts H0 then the best choice is CE. Therefore, the hypothesis is as follows:

H0 : Choose Common Effect
H1 : Choose Fixed Effect

Table 9. Selection of Common Effect and Fixed Effect Estimation Models
Source: Results of Researcher Data Processing, 2023

Chow Test	**Statistic**	**Prob F-Stat**
Cross Section F	12.996042	0.0000
Cross Section Chi Square	2257.697889	0.0000
Conclusion	Reject H0 – Choose Fixed Effect	

Based on the test results, the Cross-section Chi-square value is 2257.697889 with a P-Value of 0.0000 <0.05 so that the result is to accept H1 where Fixed Effect is a better model than Common Effect so that the next step is to test Random Effect (RE) which is then compared between RE or FE through the Hausman Test.

The next step is to conduct Random Effect (RE) testing with test results as follows:

Table 10. Random Effect Testing Results
Source: Results of Researcher Data Processing, 2023

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.054883	0.008651	6.343814	0.0000
EM (F-score)	0.000371	0.000312	1.189417	0.2345

To determine the best estimation model choice between FE or RE, the Hausman Test was conducted with the hypothesis below:

H0 : Choose Random Effect
H1 : Choose Fixed Effect

Table 11. Selection of Fixed Effect and Random Effect Estimation Models
Source: Results of Researcher Data Processing, 2023

Hausman Test	**Chi-Sq Statistic**	**Prob**
Cross-section Random	0.161381	0.6879
Conclusion	Accept H0 – Choose Random Effect	

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

The results obtained were cross-section random value of 0.161381 with P-Value: 0.6879 > 0.05 means accept H0 so it is concluded that RE is a better model than FE.

The next step is conduct a Lagrangian Multiplier Test (LM Test) to determine whether the best model is RE or CE where the hypotheses is:
H0 : Choose Common Effect
H1 : Choose Random Effect

Table 12. Selection of Common Effect and Random Effect Estimation Models
Source: Results of Researcher Data Processing, 2023

	Test Hypothesis		
	Cross-section	**Time**	**Both**
Breusch-Pagan	673.8835	6.021194	679.9047
	(0.0000)	(0.0141)	(0.0000)

Based on the LMT results, the Breusch-Pagan Cross-section value is 673.8835 with a P-Value of 0.0000 <0.05, so H0 is rejected which means that the RE model is better than CE so that the final model chosen is RE.

Random Effect Model

The Random Effect Model is perform using calculations based on the General Least Square (GLS) principle, not Ordinary Least Square (OLS) or the least squares method as in CE or FE. Thus, even though the assumption test is carried out and there is a violation of heteroscedasticity and autocorrelation, because the Random Effect Model uses calculations based on the General Least Square (GLS) principle, this assumption violation can be ignored because GLS is robust to violations of classical assumptions.

To determine the regression equation, the determination of the Coefficient Confident Interval and calculate the Individual Effects (Cross Section Effects) where the determination of the Coefficient Confident Interval is carried out by looking at the results of random effect testing (Appendix). In the test results there are lower and upper limits of the estimated coefficient tested at 95% confidence degree. The result obtained is the value of the EM estimation coefficient (F-score) of 0.000371 where in the 95% confidence degree, the estimation coefficient can be in the range of -0.000241 to 0.000983.

The individual effect or cross section effect in the RE equation will be added with an intercept, so it is in accordance with the concept of RE that RE has a constant or the same slope (estimation coefficient) for each company or individual but the intercept is different for each individual. The difference is because the constant value will be added with this individual effect which in EViews is given a symbol: [CX=R].

The results of the RE equation are obtained to answer the research hypothesis as follows:

Y_PD = 0.0548826341036 + 0.00037101872948*X_EM + [CX=R]

By using the Random Effect Regression Test results as attached, the conclusion obtained to answer the research hypothesis is the T-statistic of 1.189 (greater than 0.05) so that the result is to accept H0, which means that accrued earnings management activities do not have a significant effect on the probability of default during the COVID-19 pandemic.

The calculated F value or F-statistic is 1.404537 with a p-value or Probability (F-statistic): 0.236217 > 0.05, the result is to accept H0, meaning that all independent variables are not significant in influencing the dependent variable. The R-Squared value is 0.001255 and the Adjusted R-Square value is 0.000361, so a set of independent variables can explain the dependent variable by 0.000361 or 0.03% or less than 0.5, so the independent variable is weak in explaining the dependent variable and is not significant because the simultaneous test shows accept H0, so there are 99.97% of the value of the dependent variable which is influenced by other factors outside the independent variables in the study.

4. CONCLUSIONS AND SUGGESTIONS

Conclusions

The conclusions of this study are as follows (1) there is a difference in the number of companies that fall into the default category during the period before the COVID-19 pandemic (2019) and during the COVID-19 pandemic (2020-2021) where in 2019 there were only 42 companies in the default category (11% of the data sample) to 55 companies (15% of the data sample) in 2020 and 65 companies (17% of the data sample); (2) the industrial sectors that have the highest probability of default during the COVID-19 pandemic are the Properties & Real Estate, Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals and Industrials sectors. Meanwhile, earnings management activities are carried out by all industrial sectors; (3) The regression test results show that accrued earnings management activities have no significant effect on the probability of default during the COVID-19 pandemic. The simultaneous test results show a value of 0.03% so it is concluded that the independent variables are weak in explaining the dependent variable and are not significant where there are still 99.97% of the value of the dependent variable which is influenced by other factors outside the independent variables in the study.

Research Limitations

In the research results there are several limitations that can be input for further research as follows (1) The difference in calculation components between the KMV-Merton Model and the Dechow F-Score causes the effect between these two variables to not be well illustrated in this study. This is partly because the KMV-Merton Model emphasises the calculation of long-term changes in the market value of the company's assets, asset risk and payment of the company's contractual obligations while the Dechow F-Score takes into account changes in short-term accrual accounts such as changes in the value of cash assets, receivables, inventory, cash sales and income; (2) Although the calculation using Dechow F-Score is relevant to be used in various studies, this method is only relevant to be used to measure recording manipulation in terms of revenue and profit, so it is not relevant to be used in calculating the ability to pay in the banking industry because it does not take into account the value of payment obligations both short and long term.

Suggestions

Based on the results of the research conclusions, the suggestions that can be given to interested parties are (1) academics can conduct research development, especially related to earnings management that is relevant to the banking industry using other proxies; (2) banks can use this research to study the impact of the COVID-19 pandemic on the increase in the number of companies that fall into the default category during the crisis as well as industries that are vulnerable to falling into the default category during a crisis which can affect the level of customer Non Performing Loans; (3) OJK and BI as policy makers can anticipate, especially related to the possibility of an increase in companies and industrial sectors that fall into the default category which can lead to worsening credit quality and the potential for defaults during the crisis / pandemic.

https://doi.org/10.24912/jmieb.v7i2.24131

ISSN 2579-6224 (Versi Cetak)
ISSN-L 2579-6232 (Versi Elektronik)

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