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Investor Protection in Indonesia: Financial Ratios as Early Warning Indicators

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ABSTRACT

The Indonesian government aims to enhance public engagement in the capital market by strengthening investor protection and financial literacy through the establishment of a Watchlist Board. This study identifies the most effective financial ratios for distinguishing between the performance of LQ45 and Watchlist Board firms. Using discriminant analysis, the research examines a sample of 43 firms from the LQ45 index and 43 firms from the Watchlist Board between 2020 and 2022. The findings reveal four key financial ratios with strong differentiating power: Total Asset Growth, Return on Assets (ROA), Operating Cash Flow (OCF) to Current Liabilities, and OCF to Total Liabilities. Additionally, the study develops a predictive model that can forecast company performance and serve as an early warning system for investors. Building on prior research in this area, the results highlight the critical role of profitability, efficient resource allocation, and robust corporate governance in fostering financial stability and safeguarding investor interests. This study not only provides a practical predictive model but also offers valuable insights for interpreting these financial ratios, particularly in the context of investor protection within emerging markets, such as Indonesia.

ABSTRAK

Pemerintah Indonesia bertujuan untuk meningkatkan keterlibatan publik dalam pasar modal dengan memperkuat perlindungan investor dan literasi keuangan melalui pembentukan Dewan Watchlist. Penelitian ini mengidentifikasi rasio keuangan yang paling efektif untuk membedakan kinerja perusahaan LQ45 dan perusahaan yang terdaftar dalam Watchlist Board. Dengan menggunakan analisis diskriminan, penelitian ini menganalisis sampel yang terdiri dari 43 perusahaan dari indeks LQ45 dan 43 perusahaan dari Watchlist Board antara tahun 2020 dan 2022. Temuan penelitian ini menunjukkan empat rasio keuangan kunci yang memiliki kemampuan diferensiasi yang kuat: Pertumbuhan Aset Total, Return on Assets (ROA), Arus Kas Operasional (OCF) terhadap Liabilitas Lancar, dan OCF terhadap Total Liabilitas. Selain itu, penelitian ini mengembangkan model prediktif yang dapat memprediksi kinerja perusahaan dan berfungsi sebagai sistem peringatan dini bagi investor. Bersandar pada penelitian sebelumnya dalam bidang ini, hasil penelitian ini menekankan peran kritis dari profitabilitas, alokasi sumber daya yang efisien, dan tata kelola perusahaan yang kuat dalam mendorong stabilitas keuangan dan melindungi kepentingan investor. Penelitian ini tidak hanya menyediakan model prediktif yang praktis tetapi juga memberikan wawasan berharga untuk menafsirkan rasio keuangan ini, terutama dalam konteks perlindungan investor di pasar yang sedang berkembang, seperti Indonesia.

1. INTRODUCTION

Developing countries frequently emphasize the importance of establishing a robust banking sector to channel liquid capital into domestic markets as part of their pursuit of economic growth and development (IMF, 1994). As companies seek to invest and expand, the significance of the domestic capital market continues to grow, particularly in financing and mobilizing the long-term capital necessary for domestic development.

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However, the development of capital markets faces numerous challenges, including inadequate market infrastructure, weak or ineffective regulation and oversight, and a lack of reliable information about issuers.

Indonesia, which has recently begun to increase its per capita income to the upper middle-income level, is projected to become a high-income country by 2045 (PwC, 2023). To achieve this goal, the Indonesian government must enhance the role of capital markets in driving economic growth. Specifically, the government has set a target to increase the contribution of market capitalization to GDP to 70% by 2027 (FSA, 2023). To support this objective, the Indonesia Stock Exchange (IDX) introduced the Watchlist Board on June 12, 2023 (IDX, 2023). The Watchlist Board was established as a follow-up to the List of Equity Under Special Monitoring, which was implemented on July 19, 2021, in accordance with Regulation No. II-S on the Trading of Equity Securities under Special Monitoring. To align with the implementation of the Watchlist Board, IDX also introduced Regulation No. I-X (Kep-00081/BEI/05-2023) on June 9, 2023, governing the placement of equity securities on the Watchlist Board. Specifically, the Watchlist Board is a dedicated listing board for equities that meet the criteria outlined in Regulation No. I-X (see Appendix 1). Generally, the Watchlist Board includes stocks experiencing a decline in performance and at risk of delisting, often due to poor financial conditions, liquidity challenges, bankruptcy, or other conditions determined by IDX.

IDX has emphasized that the creation of the Watchlist Board is urgent to enhance investor protection by increasing transparency and segregating stocks that meet specific criteria onto a separate listing board. This allows investors to make informed decisions before investing (Laode, 2023). As of June 2023, the special monitoring board included 171 stocks, representing approximately 19% of all listed companies. This number is expected to grow as IDX intensifies its monitoring efforts. Meanwhile, the government is also addressing the low levels of financial literacy and inclusion in the capital market. Currently, financial literacy stands at 4.11%, while financial inclusion in the capital market is at 5.11% (Binekasri, 2023). These figures highlight the gap between financial literacy and inclusion, underscoring the importance of improving investor understanding and decision-making skills to foster rational investment choices.

Numerous studies have explored the legal protection of investors in Indonesia. These studies consistently conclude that regulators, particularly the Financial Service Authority (FSA), play a crucial role in enacting and enforcing laws to ensure effective legal protection through both preventive and repressive measures (Pradipto et al., 2019; Rahadiyan & Ambarsari, 2018; Sumadi et al., 2023). From a financial perspective, researchers have found that the implementation of Good Corporate Governance (GCG) has a positive impact on a company's financial performance (Adinegara & Sukamulya, 2021; Aries Setiawan, 2023; Athari, 2025; Iqbal & Wibowo, 2017). This highlights the connection between investor protection and the implementation of GCG, as both can be analyzed through financial ratios.

This relationship motivated the author to conduct a discriminant analysis, following the framework developed by Altman (1968), to identify the most critical financial ratios for differentiating the performance of companies on the Watchlist Board compared to those in the LQ45 index. By identifying these ratios, investors can predict a company's future financial performance, effectively serving as an early warning system to prevent poor investment decisions. This study also reviews previous research to strengthen its findings related to investor protection in emerging markets. Ultimately, this research aims not only to contribute to improving financial literacy in the Indonesian capital market but also to provide practical insights for investment decision-making.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

2.1. Agency Theory and Investor Protection in Emerging Markets

Agency theory is a foundational concept that underscores the importance of investor protection by examining the conflicts of interest that arise due to agency problems and divergent goals between shareholders (as principals) and management (as agents) (Jensen & Meckling, 1976). To address these issues, mechanisms are necessary to enable shareholders to monitor and anticipate management actions that may not align with the best interests of the principals or shareholders. Corporate governance and accounting standards are essential components of the business and financial landscape, playing pivotal roles in ensuring transparency, accountability, and ethical behavior within organizations. While corporate governance frameworks vary across countries, industries, and companies, they generally comprise a combination of laws, regulations, guidelines, and best practices. The implementation of these frameworks and standards can mitigate agency problems caused by information asymmetry between management and shareholders (Hope et al., 2007; Huang et al., 2013).

Previous research has consistently shown that legal protection for investors is a critical factor in promoting the development of a country's financial markets. Differences in legal structures and enforcement across nations lead to variations in financial development (La Porta et al., 1998). Furthermore, investor protection is closely linked to corporate governance, as weaker legal systems often result in lower levels of governance quality. For instance, Klapper and Love (2005) analyzed corporate governance ratings in 14 developing countries and found that governance levels were significantly lower in countries with weaker legal systems. This highlights the correlation between corporate governance and information asymmetry, as better governance is strongly associated with improved operational performance and market valuation (Klapper & Love, 2005). Consequently, governance challenges are more prevalent in countries with weak legal environments.

Recent studies have further explored the relationship between corporate governance and financial performance. For example, Hong et al. (2023) examined a sample of Vietnamese listed companies between 2010 and 2020 and found that corporate governance mechanisms effectively controlled earnings management. Similarly, Adinegara and Sukamulya (2021) identified a positive relationship between good corporate governance and a company's market value, including profitability (proxied by ROA), among financial sector firms listed on the Indonesia Stock Exchange (IDX) during the period 2010–2019. La Porta et al. (1998) also emphasized that ineffective legal protection and weak regulations regarding information dissemination exacerbate agency problems. In emerging markets, where investors are often less informed than their counterparts in developed markets, information asymmetry is particularly pronounced. This disparity can lead to mispricing, as managers may exploit their informational advantage to the detriment of shareholders. Cooper et al. (2008) argued that investors tend to overvalue companies with high investment projects, often overlooking potential agency problems that could negatively impact the actual value of these investments. Subsequent corrections in valuations result in lower stock returns over time. Gray and Johnson (2011) supported this view, attributing the asset-growth effect to mispricing. Rizova and Saito (2020) further explored this phenomenon, using asset growth as a proxy for corporate investment and finding a negative impact of investments in both developed and emerging markets. The effect was particularly pronounced for small-cap stocks, driven by poor performance in heavily invested companies.

Gonenc and Ursu (2018) investigated this effect in 26 emerging markets during the period 2005–2013, with a specific focus on the global financial crisis. They found that the asset growth effect was stronger during crisis years, particularly in emerging economies with weaker shareholder and creditor protections. Similarly, Iqbal and Wibowo (2017) tested the mispricing theory on 283 Indonesian listed firms during 2010–2014 and confirmed the existence of asset growth anomalies. Strong investor protection mechanisms are essential for mitigating agency problems, as they increase the cost for managers to pursue personal interests at the expense of shareholders. For instance, Hope et al. (2007) demonstrated that high-quality accounting disclosures enhance a firm's valuation by limiting management's flexibility to misuse company assets. Managers often have incentives to appropriate large sums of a firm’s cash for personal gain rather than maximizing the firm’s value. Huang et al. (2013) examined firms in 39 countries and found that the level of investor protection and accounting standards significantly influence a firm's cash holdings. Additionally, during crises in emerging markets, investors tend to place greater value on cash holdings in firms with stronger investor protections.

Athari (2025) conducted a similar study on 608 listed companies in the Asian market and found that the impact of corporate governance is more pronounced in environments with strong investor protections. This leads companies to be less inclined to hold large cash reserves, instead allocating 0.5% and 0.1% more to R&D and dividend payments, respectively, compared to other firms. Thakur and Kannadhasan (2019) analyzed a large sample of 4,236 firms from 16 emerging markets to examine the relationship between corruption and cash holdings. Their findings indicated that cash holdings are positively related to corruption. However, in high-corruption environments with low investor protection, cash adds value to firms only to an insignificant extent. Jabbouri and Almustafa (2021) reported a significant positive relationship between corporate cash holdings and firm performance among listed companies in the Middle East and North African (MENA) emerging markets between 2004 and 2018. However, the benefits of cash holdings were more pronounced in countries with strong national governance and institutional frameworks.

2.2. Discriminant Analysis

Discriminant analysis is a statistical technique used to classify or assign an observation or case into one of two or more groups based on its characteristics. Altman (1968) was among the first researchers to apply

discriminant analysis to predict bankruptcy. His study analyzed 66 manufacturing companies from the period 1946 to 1965, dividing them into two groups: 33 bankrupt companies and 33 non-bankrupt companies. Using financial ratios from the year prior to bankruptcy, Altman employed multiple discriminant analysis (MDA) to identify the five financial ratios that most effectively distinguished between the two groups. These ratios formed the basis of a predictive model for assessing the likelihood of future bankruptcy. The discriminant function model developed by Altman (1968) is presented below:

$$Z\ score = \mathrm{a} + \mathrm{Wa\ x\ a} + \mathrm{Wb\ x\ b} + \cdots .. + \mathrm{Wn\ x\ n} \quad (1)$$

where,

Z	= discriminant score
a	= intercept
Wa,b,…,n	= discriminant weight for independent variable n
a,b,…,n	= independent variable

Discriminant analysis using financial ratios has been widely applied by researchers to predict bankruptcy across various industries and countries (Altman et al., 2017; Sareen & Sharma, 2022; Toly et al., 2020). Bankruptcy assessments provide critical insights that enable governments, investors, shareholders, and management to make informed financial decisions and mitigate potential losses. Bankruptcy prediction models serve as early warning systems, signaling the likelihood of a company's financial failure. However, these models are not limited to bankruptcy prediction alone. Fundamentally, prediction models are designed to classify or categorize observations or cases into one or more groups based on their characteristics. Previous research has demonstrated that such models can also be used to forecast a company's future performance. For instance, Sareen and Sharma (2022) employed discriminant analysis to assess financial distress and predict stock prices in the Indian automotive industry. Similarly, Soekarno and Kinanthi (2020) applied discriminant analysis to differentiate the performance of U.S.-based ICT companies, categorizing them as either Investment Grade or Non-Investment Grade based on credit ratings from Moody's and S&P.

The field of bankruptcy prediction continues to grow as its applications and benefits expand. Predicting a company's future performance can help identify weaknesses long before bankruptcy becomes a possibility, enabling investors to enhance the quality of their investment portfolios. While discriminant analysis and linear regression models are among the most commonly used techniques for bankruptcy prediction, their effectiveness is often constrained by the statistical assumptions they rely on, such as linearity, normality, and independence among variables. These limitations have prompted researchers to explore alternative methods. With advancements in technology, several studies have compared the accuracy of traditional statistical methods with machine learning and artificial intelligence techniques. For example, Lee and Choi (2013) highlighted the importance of accurate bankruptcy prediction for companies across various industries, particularly for investors and creditors. Their study, which investigated Korean corporate bankruptcy using a back-propagation neural network (BNN), demonstrated higher prediction accuracy compared to multivariate discriminant analysis (81.43% for BNN versus 74.82% for MDA). Similarly, Inam et al. (2019) found that artificial neural networks (ANN) outperformed both MDA and binary logistic regression (BLR) in assessing bankruptcy risk among non-financial firms in Pakistan, achieving prediction accuracies of 90% for ANN, 85% for MDA, and 75% for BLR.

2.3. LQ45 Index and Watchlist Board

The LQ45 index is a stock market index that represents the 45 most liquid stocks listed on the Indonesia Stock Exchange (IDX). Introduced in February 1997, the index is designed to track the performance of highly liquid stocks that meet specific selection criteria (see Appendix 1). The selection process for the LQ45 index is based on market capitalization, trading liquidity, and the fundamental financial health of the companies. The index is reviewed semi-annually to ensure it reflects the most actively traded stocks in the market. Investors and analysts commonly use the LQ45 index as a benchmark to evaluate the overall performance of the Indonesian stock market. Since it consists of actively traded stocks, the index serves as an indicator of market trends. Both institutional and retail investors rely on the LQ45 index to guide their investment decisions, as it includes stocks known for their high liquidity and relative stability. By selecting stocks based on objective and transparent criteria, the LQ45 index enhances market transparency and fosters investor confidence in the Indonesian capital market.

In contrast, the Financial Services Authority (OJK) maintains a separate monitoring mechanism for "at-risk" companies, known as the Watchlist Board. This board serves as a regulatory ability to identify and monitor companies experiencing financial distress, governance issues, or low liquidity. A stock is placed on the Watchlist Board if it meets one or more of the established criteria (see Appendix 1). By publicly identifying struggling companies, the Watchlist Board promotes greater market awareness and encourages investors to exercise caution. This enhanced regulatory oversight helps investors make more informed decisions, thereby reducing uncertainty in the market. Additionally, the Watchlist Board incentivizes listed companies to maintain sound financial and governance practices to avoid being placed on the monitoring list.

2.4. Financial Ratios

The selection of financial ratios used as variables in this study is based on prior research that has demonstrated their significant influence on, or relationship to, company performance. Several of these ratios have also been shown to predict future returns or the likelihood of default, financial distress, or bankruptcy. Table 1 provides a summary of previous findings that support the selection of variables for this study.

Table 1. Related findings on financial ratios

Authors, Year	Sample; Period	Findings
Soekarno & Kinanthi (2020)	70 listed US firms in ICT sector (35 firms of Investment group & 35 firms of non-investment group); 2016-2018	There are four variables (ROA, OCF to current liabilities, debt to EBITDA, OCF to sales) that best discriminate between the groups
Nugroho (2018)	8 Indonesian listed firms in coal mining sub-sector; 2014-2016	Asset growth has positive impacts significantly with profitability (ROA, ROE, Profit margin)
Kusuma (2021)	674 Indonesian listed firms; 2019-2020	ROA can predict future investment returns
Daniella & Lukman (2023)	55 Indonesian listed firms in mining sector; 2014-2020	ROA and OCF to current liability have a positive effect on financial distress
Assagaf et al. (2021)	31 Indonesian state-owned enterprises; 2014-2018	OCF variables have a significant effect on SOEs' financial distress in Indonesia
J. C. Huang et al. (2022)	309 Taiwanese marginally distressed firms; 2003-2017	OCF indicators are reliable tools to predict the likelihood and the duration of distressed firms' survival; also, liquidity, growth, and size of the firm are important determinants in the likelihood of firm survival from financial distress
Diah & Putri (2021)	252 Indonesian listed firms in manufacturing sector; 2017-2019	OCF to current liability and sales growth had a negative effect on financial distress
Tian & Yu (2017)	108 default firms and 112 default firms in Europe; 1998-2012	Retained Earnings/Total Asset, Total Debt/Total Asset and Current Liability/Sales are bankruptcy predictor for Japan market; Equity/Total Liability is consistently selected for bankruptcy predictor for some Europe firms
Liang et al. (2016)	239 bankrupt and 239 non-bankrupt in Taiwan; 1999-2009	Among the seven ratio categories (i.e., solvency, capital structure, profitability, turnover, cash flow, growth, others), the solvency and profitability categories were the strongest predictors of bankruptcy among Taiwanese companies.
Mansikkamäki (2023)	66.000 limited firms in Finland; 2015-2018	The benefits of firm size for future performance depend on the firm's profitability

Table 2. Research variables

Ratios	Formula	Authors, Year
Current ratio	Current asset/current liability	(Y. Huang et al., 2013; Liang et al., 2016)
Cash ratio	Cash/current liability	(Y. Huang et al., 2013; Liang et al., 2016)
WC/TA	(Current asset-current liability)/total assets	(Liang et al., 2016)
Profit margin	Net income/sales	(Liang et al., 2016; Mansikkamäki, 2023; Nugroho, 2018)
Pre-tax margin	Earning before tax/sales	(Liang et al., 2016)
Basic earning power	EBIT/total assets	(Liang et al., 2016)
EBITDA margin	EBITDA/sales	(Liang et al., 2016)
Operating margin	EBIT/sales	(Liang et al., 2016; Mansikkamäki, 2023)

Ratios	Formula	Authors, Year
ROA	Net income/total assets	(Daniella & Lukman, 2023; Kusuma, 2021; Nugroho, 2018; Soekarno & Kinanthi, 2020)
ROE	Net income/equity	(Nugroho, 2018)
ROIC	Net income/ (long-term debt + equity)	(Liang et al., 2016)
D/E	Debt/equity	(Liang et al., 2016; Tian & Yu, 2017)
D/A	Debt/total assets	(Liang et al., 2016; Tian & Yu, 2017)
D/EBITDA	Debt/EBITDA	(Soekarno & Kinanthi, 2020)
OCF/CL	OCF/current liabilities	(Assagaf et al., 2021; Diah & Putri, 2021; J. C. Huang et al., 2022; Liang et al., 2016; Soekarno & Kinanthi, 2020)
OCF/TL	OCF/total liabilities	(Assagaf et al., 2021; J. C. Huang et al., 2022; Liang et al., 2016)
OCF/Sales	OCF/sales	(Assagaf et al., 2021; J. C. Huang et al., 2022; Soekarno & Kinanthi, 2020)
OCF/NI	OCF/net income	(Assagaf et al., 2021; J. C. Huang et al., 2022)
OCF/CFI	OCF/cashflow from investment	(Assagaf et al., 2021; J. C. Huang et al., 2022)
Cash-reinvested ratio	(OCF-dividend)/ (non-current asset - NWC)	(Liang et al., 2016)
RE/TA	Retained earnings/total assets	(Liang et al., 2016)
Net income growth	(Net income t - net income 0) / net income0	(J. C. Huang et al., 2022; Liang et al., 2016)
Total asset growth	(Total assets t - total assets 0) / total assets0	(J. C. Huang et al., 2022; Mansikkamäki, 2023; Nugroho, 2018)
Sales growth	(Sales t - sales 0) / sales0	(Diah & Putri, 2021; J. C. Huang et al., 2022)

Based on these findings, the author identifies 24 ratios to serve as the variables for this study. While some of these ratios are not explicitly mentioned in prior research, the author has ensured that they align with the context and objectives of the study. For example, the EBITDA-to-sales ratio is an adaptation of the EBIT-to-sales ratio, and the OCF/CFI ratio is a refinement of the CAPEX/TA ratio. A comprehensive overview of the research variables and their corresponding references to previous studies is provided in Table 2.

2.5. Hypothesis Development

Previous research has demonstrated that discriminant analysis is an effective method for identifying financial ratios that can significantly differentiate or classify company performance, making them useful for predicting future performance (Altman, 1968; Sareen & Sharma, 2022; Soekarno & Kinanthi, 2020). The financial ratios selected as research variables in this study have been shown to have a significant impact on company performance, as presented in Tables 1 and 2. Consequently, this study hypothesizes that the most significant ratios can be identified to distinguish company performance between the LQ45 Index and the Watchlist Board, enabling their use in predicting performance in new cases. Based on this premise, the hypothesis proposed in this study is as follows: Among the 24 variables analyzed, there are specific variables that most significantly differentiate performance between the LQ45 Index and the Watchlist Board.

2.6. Research Framework

Figure 1 presents the conceptual framework and highlights the intended contributions of this research. Financial ratios from LQ45 and Watchlist Board firms will be analyzed using discriminant analysis to identify the ratios that most effectively differentiate the two groups. These identified ratios will be used to develop a linear model capable of classifying or predicting future company performance. Specifically, the model will determine whether a company is likely to perform well, similar to LQ45 firms, or perform poorly, potentially facing challenges like Watchlist firms. The predictor variables derived from this analysis will then be further examined in the context of investor protection, drawing on insights from previous research. Consequently, this study not only develops a practical predictive model but also provides valuable insights into interpreting financial ratios, particularly in relation to investor protection in emerging markets such as Indonesia.

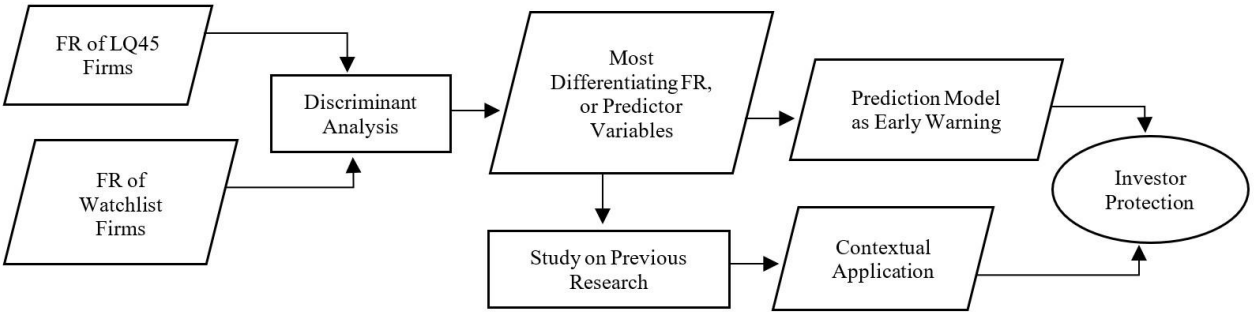

Figure 1. Research framework

3. RESEARCH METHOD

3.1. Sample

The sample for this study consists of Indonesian firms listed on the LQ45 Index and the Watchlist Board. Data collection was conducted in August 2023, with variables derived from the full-year financial statements for the period 2020–2022. This time frame was selected for several reasons. First, predictive analysis requires data from at least one year prior to financial distress or bankruptcy to ensure greater predictive accuracy (Altman, 1968; Liang et al., 2016; Soekarno & Kinanthi, 2020). Second, this period encompasses the COVID-19 pandemic and the subsequent post-pandemic recovery, a critical time during which investors needed to exercise caution in making investment decisions amidst economic uncertainty. The sample selection was conducted using purposive sampling based on the following criteria: (1) availability of full-year financial statements for 2020–2022: Two LQ45 firms were excluded due to incomplete financial statements, resulting in a sample of 43 out of 45 LQ45 firms. For the Watchlist Board, 88 firms met this criterion. However, in discriminant analysis, an unequal number of samples between groups can lead to class imbalance, which may degrade the accuracy of the final prediction model (Altman, 1968; Liang et al., 2016). To address this issue, an equal number of samples (43 firms) was selected from the Watchlist Board; (2) criteria for Watchlist Board firms: Sampling for the Watchlist Board was based on the number of criteria each company met, as determined by the Indonesia Stock Exchange (IDX). Firms meeting more criteria were assumed to be in poorer financial condition and to exhibit weaker performance. This approach ensures a balanced and representative sample for the analysis.

3.2. Software

Discriminant analysis in this study will be conducted using JASP software. JASP is an open-source graphical software package designed for basic statistical procedures, such as t-tests, ANOVAs, and contingency table analysis. Additionally, JASP includes machine learning functionalities, such as regression, classification, and clustering analysis (Wagenmakers et al., 2018). These analyses are implemented in R and utilize a series of R packages (Love et al., 2019). Previous research has demonstrated that machine learning methods often yield improved accuracy in discriminant analysis compared to traditional statistical approaches (Inam et al., 2019; S. Lee & Choi, 2013). Based on these findings, the authors are confident that the results of this study will be both accurate and reliable.

4. DATA ANALYSIS AND DISCUSSION

4.1. Discriminant Analysis Result

The summary statistics for both groups are presented in Table 3. An analysis of the means reveals that margin and return ratios are significantly higher for LQ45 firms compared to Watchlist Board firms, highlighting the profitability challenges faced by the Watchlist Board. Profitability directly impacts a firm's ability to generate cash flow and sufficient operating profits to service its debts. However, an opposite trend is observed in the current and cash ratios, where Watchlist Board firms exhibit higher liquidity than LQ45 firms.

At first glance, it may seem counterintuitive that Watchlist Board firms have higher liquidity ratios than LQ45 firms. However, this pattern aligns with the typical financial behavior of distressed companies. High liquidity in Watchlist Board firms often reflects inefficiency, precautionary cash hoarding, or restricted access to credit, rather than financial strength. In contrast, LQ45 firms maintain a balance between liquidity

and growth, demonstrating effective financial management. Additionally, the low standard deviations in LQ45 firms indicate a level of predictability that appeals to risk-averse investors. On the other hand, the high variability in Watchlist Board firms signals greater uncertainty, attracting speculative investors willing to take risks on the potential recovery of distressed companies.

In classical discriminant analysis, all independent variables must first be tested to ensure they meet the assumption of no multicollinearity. If any variables exhibit high collinearity, they must be excluded from further analysis. The remaining independent variables are then tested to confirm they meet additional assumptions, including multivariate normal distribution, equality of variance-covariance matrices across and within groups, and mutually exclusive group membership. Once all these assumptions are satisfied, the discriminant analysis can proceed.

Table 3. Statistics summary of financial ratios

Ratios	LQ45 Index				Watchlist Board			
	Mean	Median	Std. Dev	Var	Mean	Median	Std. Dev	Var
Current ratio	2.31	1.56	4.39	19.26	3.19	0.82	23.69	561.09
Cash ratio	1.04	0.47	2.31	5.34	1.72	0.04	20.36	414.67
WC/TA	0.15	0.12	0.19	0.04	-5.29	0	58.94	3473.81
Profit margin	0.14	0.12	0.33	0.11	-160.04	-0.16	2287.1	5230845.93
Pre-tax margin	0.22	0.17	0.36	0.13	-60.32	-0.04	848.25	719524.88
Basic earning power	0.11	0.09	0.11	0.01	-0.48	-0.01	4.23	17.89
EBITDA margin	0.3	0.25	0.48	0.23	-29.47	0.04	391.73	153452.63
Operating margin	0.22	0.18	0.37	0.14	-62.1	-0.04	848.58	720088.32
ROA	0.07	0.05	0.09	0.01	-0.36	-0.04	2.34	5.49
ROE	0.15	0.13	0.22	0.05	-3.51	0	39.63	1570.52
ROIC	0.11	0.07	0.17	0.03	-0.14	-0.01	9.9	98.09
D/E	0.55	0.29	0.89	0.79	1.42	0.31	7.91	62.64
D/A	0.19	0.17	0.19	0.04	17.91	0.32	220.25	48508.92
D/EBITDA	1.9	0.78	3.37	11.38	4.19	0.09	99.09	9819.43
OCF/CL	0.88	0.67	0.96	0.91	0.35	0	2.51	6.28
OCF/TL	0.37	0.23	0.53	0.28	0.07	0	1.22	1.49
OCF/Sales	0.25	0.19	0.71	0.51	-27.47	-0.01	400.7	160561.21
OCF/NI	3.15	1.46	13.68	187.02	5.29	0.07	109.28	11942.81
OCF/CFI	-234.13	-1.54	3371.67	11368160.31	-0.55	-0.2	82.11	6742.77
Cash-reinvested ratio	0.12	0.08	0.33	0.11	0.29	0	3.44	11.81
RE/TA	0.31	0.24	0.24	0.06	-36.62	-0.16	406.08	164899.02
Net income growth	-0.02	0	5.26	27.68	-4.97	-0.03	49.64	2463.98
Total asset growth	0.15	0.05	0.49	0.24	0	0	0.54	0.29
Sales growth	0.13	0.04	0.67	0.45	0.19	0	3.09	9.53

Table 4. Linear discriminant classification

Linear Discriminants	Method	n(Train)	n(Test)	Test Accuracy
1	Moment	344	86	0.895

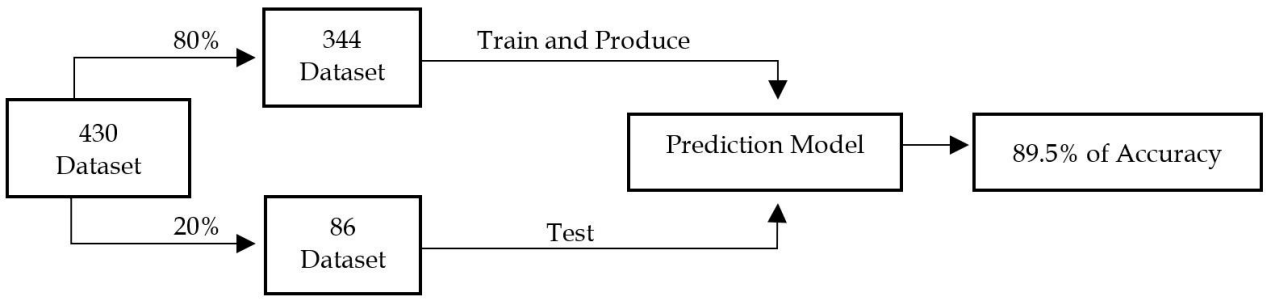

Figure 2. Linear discriminant classification

Discriminant analysis in this study was conducted using machine learning software, which differs from the traditional approach of using classical statistical software. In this research, the discriminant analysis was performed using a training-based method. Unlike the classical approach, the training method does not require classical assumption testing. However, both classical statistical methods and training-based methods aim to address the same fundamental question: identifying the discriminant function model that predicts group membership. During the data preparation stage, the data was profiled, formatted, and structured to ensure it was ready for model training. This stage also involved processes such as normalization, removing duplicates, and correcting errors. Once prepared, the data was divided into two subsets: one for training the model and the other for testing or evaluation. This division marks a key difference between classical statistical discriminant analysis and the training-based approach.

In this study, the model training followed an 80:20 split, where 80% of the data was used to train and develop the model, while the remaining 20% was reserved for validation. This 80:20 split is a widely accepted standard in machine learning, as it ensures that the majority of the data is used for training, allowing the model to effectively learn patterns. The remaining 20% is used to validate the model, helping to prevent overfitting—where a model performs well on training data but poorly on unseen data. Training the machine learning model involves inputting a large number of datasets, which significantly enhances prediction accuracy. During this process, the algorithm is refined and optimized to improve its performance. Figure 2 illustrates the training and testing process used in this research.

Table 4 indicates that 344 datasets were used for training, while 86 datasets were reserved for testing. All 24 financial indicators, or independent variables, were included in both the model training and testing processes. The discriminant analysis achieved an accuracy rate of 89.5%, demonstrating strong predictive and classification capabilities for new cases. The remaining 10.5% represents the likelihood of classification errors.

Table 5. Tests of equality of class means

Variable	F	df1	df2	P
Current	0.286	1	428	0.593
Cash	0.238	1	428	0.626
WC/TA	1.830	1	428	0.177
Profit margin	1.055	1	428	0.305
Pre-tax margin	1.095	1	428	0.296
Basic earning power	1.187	1	428	0.061
EBITDA margin	1.241	1	428	0.266
Operating margin	1.160	1	428	0.282
ROA	7.290	1	428	0.007
ROE	1.836	1	428	0.176
ROIC	0.130	1	428	0.719
D/E	2.540	1	428	0.112
D/A	1.391	1	428	0.239
D/EBITDA	0.114	1	428	0.736
OCF/CL	8.306	1	428	0.004
OCF/TL	10.636	1	428	0.001
OCF/Sales	1.028	1	428	0.311
OCF/NI	0.081	1	428	0.776
OCF/CFI	1.031	1	428	0.310
Cash reinvested	0.512	1	428	0.475
RE/TA	1.779	1	428	0.183
Net income growth	2.120	1	428	0.146
Total asset growth	9.362	1	428	0.002
Sales growth	0.072	1	428	0.789

Table 6. Linear discriminant coefficient

Variable	F
(Constant)	2.568
ROA	7.218
OCF/TL	1.335
OCF/CL	0.513
Total asset growth	0.174

Table 5 evaluates whether the independent variables can effectively distinguish between the two dependent variables. The primary goal of discriminant analysis is to identify the variables that best differentiate the groups. Variables with significant differences in their means are stronger predictors of group membership. The equality of class means test determines whether the differences in the averages of the predictor variables between the two groups are statistically significant. The null hypothesis for this test states that the means of a predictor variable are equal across the groups, indicating that the variable does not significantly contribute to distinguishing between them.

The F-statistic measures the extent to which the group means differ relative to the variability within the groups. Higher F-values indicate greater differences in means, suggesting that the variable is more effective at separating the groups. The p-value assesses the statistical significance of these differences. A p-value less than 0.05 indicates that the variable's mean differs significantly between the groups, making it a valuable predictor for discrimination. Conversely, variables with p-values greater than 0.05 have means that do not differ significantly between the groups, contributing minimally to the discriminant function and being less important for classification.

The significance of the p-value is crucial in determining whether the hypothesis is supported. To support the hypothesis, a p-value of less than 0.05 is required. The regression results indicate that not all independent variables meet this threshold. Only the independent variables with p-values below 0.05 are capable of significantly differentiating between the two groups. These variables include return on assets (ROA), total assets growth, operating cash flow to current liabilities (OCF/CL), and operating cash flow to total liabilities (OCF/TL).

Table 3 also highlights an important observation: ratios with large mean differences, such as profit margin, debt-to-assets (D/A), and operating cash flow to sales (OCF/Sales), do not necessarily have the ability to significantly differentiate between the two groups. Similarly, ratios with high variability, such as EBITDA margin, debt-to-assets (D/A), and retained earnings to total assets (RE/TA), are less likely to serve as effective predictors or differentiators. This underscores the importance of statistical significance over raw differences or variability when identifying meaningful predictors.

The four ratios identified in this study are presented in Table 6 and serve as predictors when used together in a discriminant model. The coefficients represent the weights assigned to each variable in the discriminant function, with larger coefficients indicating a stronger contribution to distinguishing between the groups. Among the variables, return on assets (ROA) has the highest coefficient (7.218), making it the strongest predictor. Operating cash flow to total liabilities (OCF/TL) follows as the second most influential variable (1.335), while operating cash flow to current liabilities (OCF/CL) has a moderate influence (0.513). Total asset growth, with a coefficient of 0.174, contributes the least statistically to the model. All coefficients are positive, indicating that higher values for these ratios are associated with classification into the leading performers group (LQ45). Conversely, lower values for these ratios are linked to classification into the Watchlist Board group, reflecting weaker financial performance.

4.2. Practical Implications of the Discriminant Function

As a result, the discriminant analysis prediction model developed in this study is presented as follows:

$$Z\ score = 2.568 + 7.218\ \text{Return on Asset} + 1.335\ \text{OCF to Current Liabilities} + 0.513\ \text{OCF to Current Liabilities} + 0.174\ \text{Total Asset growth} \quad (2)$$

The purpose of this model is to predict the future performance of a company by calculating its Z-score. In this study, a cut-off value of 0 is established. A positive Z-score ($Z > 0$) indicates that the company is predicted to perform well in the future, while a negative Z-score ($Z < 0$) suggests that the company is likely to underperform and may experience financial distress.

The Z-score derived from the discriminant function provides a practical ability for classifying firms into one of two groups. A positive Z-score signals strong future performance, whereas a negative Z-score serves as an early warning of potential financial distress. This model not only aids investors in making informed decisions by identifying early signs of distress but also supports policymakers in monitoring market stability and prioritizing regulatory interventions. By focusing on four key financial ratios, the model bridges the gap between theoretical financial analysis and practical application. It contributes to enhanced investor

protection and improved financial literacy, particularly in the context of an emerging economy like Indonesia.

4.3. Discussion on the Predictor Variables

4.3.1. Return on Asset (ROA)

In this study, ROA emerges as a strong predictor of company performance, consistent with the findings of Daniella and Lukman (2023), Kusuma (2021), and Soekarno and Kinanthi (2020). Despite its widespread use in both academic research and business practice, some argue that ROA, as an earnings indicator, is less reliable because it is derived from accounting and estimation figures. As a result, cash flow is often preferred. This debate has been highlighted in previous studies. For instance, Nallareddy et al. (2020) found that cash flows consistently outperform earnings in predicting future cash flows. Similarly, J. E. Lee et al. (2017) demonstrated that operating cash flow (OCF) is a better predictor of stock returns than earnings. Conversely, some researchers argue that using operating earnings instead of "bottom-line" earnings yields better results than OCF. This perspective is supported by Noury et al. (2020), who found that accrual-based accounting methods are more effective than cash-based accounting methods in forecasting future cash flows. Notably, Lee et al. suggested that during periods of financial crisis or distress, OCF has a stronger relationship with stock returns. In such situations, investors are advised to place greater emphasis on OCF information rather than earnings information.

Rathnayake and Sun (2017) further highlighted that ROA has significant positive relationships with corporate governance measures. This suggests that good corporate governance (GCG) mechanisms are essential for enhancing the reliability of financial information. According to Aries Setiawan (2023), improving information equality can enhance the quality of profitability data. Implementing robust corporate governance practices, such as establishing an audit committee, can mitigate the risks of earnings management (Hong et al., 2023). Healthy companies with strong governance mechanisms are generally more reliable than financially distressed firms (Adinegara & Sukamulya, 2021). The absence of GCG disclosures poses significant risks, particularly for small investors who often have limited access to information (Sukamulja, 2004). Therefore, ensuring transparency and accountability through effective governance practices is critical for fostering trust and improving the quality of financial reporting.

4.3.2. OCF to Current Liabilities and OCF to Total Liabilities

In this study, two OCF ratios are identified as predictor variables: OCF to current liabilities (OCF/CL) and OCF to total liabilities (OCF/TL). OCF/CL measures a company's ability to generate cash internally to meet its short-term obligations, while OCF/TL reflects its capacity to address long-term debt. These findings align with previous research highlighting the significant relationship between OCF and financial distress, where OCF is recognized as a strong predictor of financial distress (Assagaf et al., 2021; J. C. Huang et al., 2022; Soekarno & Kinanthi, 2020). Daniella and Lukman (2023), as well as Diah and Putri (2021), noted that OCF/CL, which focuses on short-term liabilities, has a greater influence on financial distress. However, in this study, OCF/TL demonstrates a stronger predictive ability than OCF/CL.

A higher OCF provides companies with greater flexibility in utilizing cash for investments, dividend payments, or loan repayments. This flexibility, in turn, influences the level of cash held by the company. Determining the appropriate level of cash holdings is crucial to avoid potential agency problems. Thakur and Kannadhasan (2019) argued that excess cash creates opportunities for corruption, particularly in environments with low levels of investor protection. In emerging markets like Indonesia, where investor protection and information equality remain relatively weak, excessive cash holdings are more prone to agency problems.

This concern is further supported by Jabbouri and Almustafa (2021), who found a significant positive relationship between corporate cash holdings and firm performance. They suggested that strong national governance, reinforced through enhanced investor protection, can reduce agency problems and increase the value of cash holdings. Interestingly, Athari (2025) observed that companies with stronger governance mechanisms tend to hold less cash and allocate more cash toward research and development (R&D) and dividend payments. This indicates that robust corporate governance (GCG) mechanisms not only mitigate agency problems but also promote growth by encouraging more productive uses of cash.

4.3.3. Total Asset growth

The asset growth rate is a widely used financial ratio in investor protection research across both developed and developing countries, and it has yielded significant findings. Nugroho (2018) identified a significant positive effect of asset growth on profitability. However, in this study, the debt ratio did not emerge as a distinguishing variable. Asset growth driven by internal funds was found to have a greater influence on profitability than asset growth driven by debt. This highlights the importance of asset efficiency in generating profitability. Additionally, debt that is not balanced with profitability can place a financial burden on the company. This mutually influential relationship is further supported by Mansikkamäki (2023), who found that profitable companies are more likely to reinvest their earnings into new assets, thereby contributing to overall asset growth.

Nevertheless, investors should carefully evaluate asset growth, particularly in companies with significant investments during times of crisis. An early study by Cooper et al. (2008) suggested that the asset growth effect is often attributable to mispricing. Companies experiencing substantial increases in asset growth or making large investments over a specific period are at a higher risk of declining returns in subsequent periods. Consistent with these findings, Gonenc and Ursu (2018) provided empirical evidence supporting the mispricing hypothesis, particularly in emerging markets with lower levels of investor protection. Similarly, Rizova and Saito (2020) highlighted the poor performance of heavily invested companies, which is a common occurrence in emerging markets. Furthermore, Iqbal and Wibowo (2017) observed anomalies in the Indonesian capital market, attributing them to mispricing caused by investor overreaction and psychological biases.

5. CONCLUSION, IMPLICATION, SUGGESTION, AND LIMITATIONS

This study emphasizes the pivotal role of investor protection in enhancing capital market efficiency and fostering investor confidence. By analyzing the implementation of the Watchlist Board in Indonesia, the research demonstrates how regulatory initiatives can function as an early warning system for financial distress. The findings reveal that key financial ratios—such as ROA, Total Asset Growth, OCF to Current Liabilities, and OCF to Total Liabilities—are effective in distinguishing well-performing companies from those at risk of financial instability. These results highlight the importance of financial transparency and robust governance in mitigating investment risks. Strong investor protection mechanisms not only enhance market efficiency but also encourage greater public participation in the capital market. Additionally, the study underscores the critical need for improved financial literacy, as a well-informed investor base is essential for maintaining a resilient and dynamic market.

For investors, the predictive model developed in this research provides a practical ability for evaluating company performance and making informed investment decisions. From a policy perspective, the findings suggest that regulators should continue refining monitoring frameworks to ensure that investors have access to timely and reliable financial information. Future research could explore additional factors influencing investor protection, such as the role of institutional investors, corporate governance practices, and macroeconomic conditions. Expanding the scope of analysis to include longer time horizons and cross-country comparisons would further deepen the understanding of investor protection dynamics in emerging markets. Ultimately, strengthening investor protection mechanisms remains a critical priority for fostering sustainable capital market growth and supporting broader economic development.

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Appendix 1. Criteria for LQ45 Index and Watchlist Board

A. Criteria for Inclusion in the LQ45 Index

To be included in the LQ45 index, stocks must meet the following criteria:

- Be listed on the Indonesia Stock Exchange (IDX) for at least the past three months.
- Demonstrate a healthy financial condition and strong growth prospects.
- Maintain a high market capitalization over the past one to two months.
- Rank among the 60 stocks with the highest transaction value over the last 12 months.

From these 60 stocks, the top 30 will be selected for inclusion in the LQ45 index. The remaining 15 stocks will be chosen based on additional criteria, including the number of trading days, transaction frequency, and market capitalization.

B. Criteria for Transfer to the Watchlist Board

A listed company may be transferred from its initial listing board (Main Board, Development Board, or Acceleration Board) to the Watchlist Board if it meets one or more of the following criteria:

- The company's average share price over the last six months on the Regular Market and/or Periodic Call Auction Regular Market is less than IDR 51 (this criterion does not apply to shares listed on the Acceleration Board).
- The company's most recent audited financial report received a disclaimer opinion.
- The company has not recorded any revenue, or there is no change in revenue between its latest audited financial statements and/or interim financial statements compared to previously submitted financial statements.
- If the company is a mining company or the parent company of a mining company, it has not generated revenue from its core business by the fourth fiscal year since being listed on the IDX.
- The company's most recent financial statement shows negative equity.
- The company fails to meet the requirements for remaining listed on the IDX as stipulated in Regulation No. I-A (for companies listed on the Main Board or Development Board) or Regulation No. I-V (for companies listed on the Acceleration Board).
- The company has low liquidity, defined as an average daily transaction value of less than IDR 5 million and an average daily transaction volume of less than 10,000 shares over the last six months on the Regular Market and/or Periodic Call Auction Regular Market.
- An application for suspension of debt payment obligations (PKPU), bankruptcy, or cancellation of a settlement plan has been filed against the company, and based on the IDX's assessment and/or the company's disclosure of information, such an application has a material impact on the company's condition.
- The company has a subsidiary that materially contributes to its revenue, and an application has been filed against the subsidiary which, based on the IDX's assessment and/or the company's disclosure of information, has a material impact on the company's condition.
- The trading of the company's securities has been temporarily suspended for more than one exchange day due to trading activities.
- The company meets any other conditions determined by the IDX based on the approval or order of the Financial Services Authority (Otoritas Jasa Keuangan or "OJK").

The IDX began listing companies on the Watchlist Board on June 12, 2023. Before transferring a company to the Watchlist Board, the IDX must announce the change in listing at least one exchange day prior to the transfer. Similarly, the IDX must announce the removal of a company from the Watchlist Board back to its original listing board.