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Stock Return Prediction Model in Indonesia

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Abstract
Stock returns are influenced by various things both external and internal. External factors that influence it include market sentiment and the circulation of information about the economy of the company's industry sector. Market sentiment is a reflection of the attitude and mood of investors towards the company. As a result, other investors try to anticipate the consequences of this attitude, so strategies emerge in investing. One of the strategies is the momentum of when to buy or sell an investment as a result of the investor's consideration of a situation to make their financial decision-making processes. This research aims to develop a model based on momentum estimations to determine when to buy and sell from each investment. Specifically, the study focuses on analysing the impacts of momentum factors along with beta, alpha and total risk factors on equity returns in Indonesia, using logistic regression to predict the likelihood of the returns. By combining influential factors, this model can make predictions with an accuracy of 85.6 per cent. The study has implications for investment strategy in Indonesia, particularly during episodes of downturn. The research is limited due to its reliance on the logistic regression model. This is the first study to include a momentum factor, along with beta, alpha, and total risk to predict the likelihood of equity returns in Indonesia.

Keywords— *Investment; Momentum; Return Prediction; Emerging Markets*

Abstrak
Return saham dipengaruhi oleh berbagai hal baik eksternal maupun internal. Faktor eksternal yang mempengaruhinya antara lain sentimen pasar dan beredarnya informasi mengenai perekonomian sektor industri perusahaan. Sentimen pasar merupakan cerminan dari sikap dan suasana hati investor terhadap perusahaan. Akibatnya, investor lain berusaha mengantisipasi akibat dari sikap tersebut, sehingga muncullah strategi-strategi dalam berinvestasi. Salah satu strategi tersebut adalah momentum kapan waktu yang tepat untuk membeli atau menjual suatu investasi sebagai hasil pertimbangan investor terhadap suatu situasi untuk melakukan proses pengambilan keputusan keuangannya.Penelitian ini bertujuan untuk mengembangkan model berdasarkan estimasi momentum untuk menentukan waktu yang tepat untuk membeli dan menjual dari setiap investasi. Secara khusus, penelitian ini berfokus pada analisis dampak dari faktor momentum bersama dengan faktor beta, alpha dan risiko total terhadap return saham di Indonesia, dengan menggunakan regresi logistik untuk memprediksi kemungkinan return tersebut. Dengan menggabungkan faktor-faktor yang berpengaruh, model ini dapat membuat prediksi dengan akurasi 85,6%. Penelitian ini memiliki implikasi terhadap strategi investasi di Indonesia, terutama selama periode penurunan.Penelitian ini terbatas karena ketergantungannya pada model regresi logistik. Penelitian ini merupakan penelitian pertama yang memasukkan faktor momentum, bersama dengan beta, alpha, dan risiko total untuk memprediksi kemungkinan imbal hasil saham di Indonesia.

Kata kunci— *Investment; Momentum; Return Prediction; Emerging Markets*

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I. INTRODUCTION

While emerging nations such as Russia and China continue to make the headlines nowadays with events such as the Russian-Ukraine crisis and the China-U.S. trade wars, other emerging markets such as Indonesia, are not left apart neither, with various impacts observed in the Asia Pacific region. For instance, Purwono *et al.* (2022) found U.S. tariffs on Chinese goods have a negative spillover effect on Indonesian exports. This suggests that the financial markets continue to exist in an intertwined marketplace, affected by various financial news. Importantly, noise in financial markets allow for opportunities, where emerging markets become an attraction for foreign and local investors to take advantage of price fluctuations in the stock market. Price fluctuations become an opportunity for investors or brokers who can make informed decisions by using appropriate techniques. For example, Gurrib *et al.* (2022) found that the use of popular techniques such as Fibonacci retracements resulted in higher returns than a naïve buy-and-hold model. In the same spirit, our study will attempt to create a predictive model by combining several variables that have different and interrelated functions. This study addresses the existing gap in emerging markets such as Indonesia, by proposing a model involving the combination of alpha, beta, total risk (VAR) and Momentum (MoM) to predict stock returns in Indonesia.

This research relies heavily on the Modern Portfolio Theory (MPT), first proposed by Markowitz (1952), and which till date has been adopted by various researchers in the world (see for example Scala *et. al*, 2019; Platanakis *et al.*, 2018; Platanakis & Urquhart, 2019; Gurrib, and Elsharief & Kamalov, 2020). Beta, a measure of the level of sensitivity between assets and market index was initially advocated with Sharpe developing the Capital Assets Pricing Model (CAPM). Similarly, Alpha, proposed by Jensen (1968), postulates the expertise of investment managers to increase the return of investment managed funds. It is found that the higher the alpha, the greater the attractiveness of the investment product offered. Likewise, total risk (VAR) is a variant of price movements for a specific period. Research examining the risk of individual assets can be witnessed in Litzenberger and Ramaswamy (1979), where the advantages of VAR lie in its ability to detect the level of risk from price movements in a given period. Due to the fact that price movements affect investors' returns through portfolio positive and negative returns, a reliable model is needed to detect assets that will enter the portfolio so that there is less likelihood of losses. The last variable is momentum (MoM) which was first studied by Jegadeesh and Titman (1993). Results of the study suggest investments have their own strategies for profit buying groups of assets that became profitable in the past period and selling groups of assets that underperformed in the past as a form of anticipation of future losses. Momentum is also utilized by small-funded investors as described in Hendricks, Patel, & Zeckhauser (1993) and Goetzmann & Ibbotson (1994).

Momentum strategies have given good performances to mutual fund management (Blanchett, 2019). Momentum also performed well on mid-sized investments on the Australian stock market (Hurn & Pavlov 2003). Importantly however, the effect of momentum does not work optimally on the composition of stocks derived from various industries, but rather it occurs because of the variety of industries which can bring high anomalies in a portfolio. It is best to choose one particular industry on the application of momentum for maximum results (Moskowitz & Grinblatt, 1999). With Hidden Markov Model (HMM) momentum strategy being more competitive than conventional strategy, future momentum strategies can apply artificial intelligence in capturing existing momentum (Ryou *et al.*, 2020).

Ayub *et al.* (2020) added momentum variables in the CAPM so that it includes 6 factors in pricing assets to be invested. Momentum strategies applications have extended beyond equity asset classes with uses in foreign currency markets (LeBaron, 1999). Since the early 1990s, studies of Rouwenhorst (1998) and Asness *et al.* (1997) have documented support regarding the advantage of using momentum strategies for investment in non-emerging market stocks. Griffin *et al.* (2003) found that stock markets in emerging market countries found momentum effects, where that momentum occurs due to economic improvement after the country recovers from an economic recession. Furthermore, momentum can also be applied to investments in corporate bonds and government bonds. In the following year, bonds in emerging markets have also shown momentum effects. Finally, the momentum effect has been determined to exist during the economic boom and in times of recession (Jostova *et al.,* 2013; and Luu & Yu, 2012).

Aguet, Amenc, & Goltz (2018) select factors to form a portfolio in general to improve information on market conditions and assets, and to minimize errors (risks) in investment decisions. Adjustment of industry type, value, size and momentums in assets also become factors that make it easier for investors to choose assets to invest (Asness *et al.,* 2000). These results are in line with research by Novy-Marx (2013) who reported that assets grouped in the industrial sector, momentum and profitability performance deliver superior performance compared to assets that are not grouped. The implementation of momentum strategies provides investors with benefits in investment in corporate bonds, with the return received by investors being adjusted for the level of risk (Bektic, 2018). Momentum in bonds was successfully studied in Non-Investment Grade (NIG) bonds in Europe, where the return generated increases when bonds are used for business expansion that generates NIG bonds (Barth *et al.*, 2017).

This study found a research gap that can add to the wealth of science and can be applied practically by individual investors to choose the types of assets to be invested to obtain a positive return, commensurate with a risk that can be tolerated by investors. The model offered is able to predict the best return (alpha) above the market by combining variables consisting of beta, alpha, total risk, and momentum. Moreover, the return will be classified into "good" and "bad" return by numbering them respectively to 1 and 0. This model will use logistic regression model which have been studied in finance to predict the likelihood of the return (see Upadhyay, 2012; Wang, 2014; Ali *et al.* (2018), and financial distress (Kumar & Ravi, 2007; and Chen, 2011). This method generates binary codes 1 and 0, which indicate premium returns above and below market levels. Our model also minimizes the rate of asset tracking errors that cause losses on investments made.

The momentum-based investment strategy is based on the philosophy of reducing investment losses and letting the winners thrive. The concept of momentum investing suggest that short term performance is repeated with winners continuing to be winners and losers continuing to be in the same state. It is observed that high momentum is observed in markets when the price advances or declines over a wide range in a short period of time. A momentum strategy becomes beneficial as there is no need to identify an undervalued asset and wait for market to recognize the fact to derive profits. It also facilitates the creation of potential for high profits within a short span of time.

It is observed that most large asset managers add alpha strategies to their portfolios as additional return drivers, since it facilitates diversification. Strategic beta investment strategy based on leveraging the goals of both active and passive investment can become an attractive alternate strategy for investors focusing on inexpensive, diversified equity exposure which can beat market returns. A combination of alpha and beta strategy facilitates investors to passively generate long term returns from investing in the market as a whole, with the focus turned on uncorrelated risk in order to boost overall returns. The use of total risk is useful for institutional investors such as pension funds which has a multi-asset class portfolio, and which needs to measure its exposure to a variety of risk factors.

II. LITERATURE REVIEW

Before undertaking any analysis, it is crucial to further understand the different measures used, i.e. beta, alpha, total risk and momentum determinants.

Beta - Beta is a method that measures the level of risk of asset price movements compared to the market as a benchmark. The greater the beta value of an asset, the higher the likelihood that asset price movement will overestimate the market price movement, which means that the asset is at risk in the event of a decline in the market. Therefore, this beta variable needs to be included in a useful model for investor anticipation in asset selection. This study expects that beta influences the prediction of stock returns in Indonesia. Asness, Frazzini & Pedersen (2014) find that low beta strategies tailored to their industries can generate positive returns in portfolio construction. Bender *et al.* (2016) suggest that investors can gain useful information by adopting smart beta strategies using portfolio formation with time variations. Beta research conducted in Indonesia can be seen in Salim *et al.* (2020), Waspada & Salim, (2020), and Salim & Rizal (2021).

Alpha- Alpha is primarily an indicator to measure the performance of an investment as compared to an appropriate benchmark index. It signifies how the return on the investment during a specified time period outperformed the market by average. In other words, alpha measures the extent to which an actively managed fund or alternatively weighted index beats the chosen benchmark. If connected with the performance of managed funds by investment managers, then it offers more incentive for managers to generate higher alpha values for each client. Our research hypothesizes that Alpha influences the prediction of stock returns in Indonesia. Salim *et al.* (2020) and Salim & Rizal (2021) are proponents of using alpha in their respective studies in Indonesia.

Total risk (VAR) - Since any asset price movement can provide gains or losses to investors, VAR variables can be significant contributors. For instance, a high VAR value indicates a high price change in a certain period, and it results in an asset classified as high risk. If investors are too late to realize the movement of the decline in the price of the asset it can potentially result in investment losses. This research work examines the role of total risk as a determinant of stock returns in Indonesia. An investment manager needs to adjust to the risks specified by the investor and offer an investment product that matches the chosen risk (see for example Rao *et al.*, 2018; Haugen & Heins, 1975; Fogler, 1982; Hammoudeh *et al.,* 2013; and Borri, 2019).

Momentum factor – MoM - Jegadeesh & Titman (1993) explained that momentum strategies can be determined based on periods of 1, 3, 6, 9, and 12 months based on returns on the previous period before portfolio construction. The selection of investments in assets needs to pay attention to MoM, such as ahead of the General Meeting of Shareholders (GMS). Usually when decisions of the GMS approve the distribution of dividends because there is an increase in the company's profit, this information is announced to the market. Resultingly, investors capture positive information by racing to buy the asset which makes the price of the asset rise in the market. Momentum can also be seen from the price trend in the previous period so that it can be a factor that can be used to predict the price movement of an asset for the future. Therefore, this research expects that momentum has an effect on the prediction of stock returns in Indonesia. Griffin *et al.* (2005) studied an effective momentum strategy runs over a 1-year term in emerging markets and non-emerging markets, which means that momentum investments must be actively managed to reduce investment losses caused by a decrease in the performance of the asset after it is owned.

III. RESEARCH METHODOLOGY

This study uses montly stock price data from 2009 to 2019 based on 353 stocks in Indonesia, resulting in 40,499 prices. The Jakarta Stock Exchange Composite Index (JCI), which is a major stock market index in the emerging market, tracks the performance of all companies listed on the Indonesia Stock Exchange. It is constructed using a modified capitalization-weighted index. The Jakarta Stock Price Index has a base value of 100 as of August 1982. As per Trading Economics (2022), during the period 2009-2022, the JCI experienced a significant drop in index values during the early COVID-19 impact of January-March 2020. Otherwise, the market index has been trending upward with an increase of over 200 per cent over the 2009-2019 period. Similarly, before 2009, the JCI index was negatively affected by the global financial crisis of 2008. Both the global financial crisis and early COVID-19 impacts are excluded from our analysis, due to our selected period of study (2009-2019). The data is sourced from Factset database.

Logistic regression was chosen because it can produce constant values that can predict the state with the variables used in this study. For instance, Kamalov, Gurrib & Rajab (2021) used logistic regression as a popular classification algorithm as the basis of their forecasting model and found stock price and stock return are important input features in determining direction of price movements in US large-capitalized stocks. Logistic regression is used where stock returns are categorized into binary 1 and 0. Code 1 states that the return of the stock exceeds the return obtained by the market, then zero per cent of the return obtained is below the market return. The logistic regression, as a linear based model, can be found decomposed as follows:

$$\hat{q} = \frac{1}{(1+e^{-z^T x})} \qquad (1)$$

, where $\hat{q}$ is the predicted value, z is the vector of the model weights and x is the vector of the features. The logistic regression model has a convex cost function, ensuring that a unique global minimum exists. As a linear regression, it is robust to overfitting. Although it cannot fit non-linear patterns, this does not affect our study as we assume a linear relationship among the different variables. Despite that there are more advanced algorithm-based models such as multilayer perceptrons, long-short term memory and random forest (Ballings *et al.*, 2015), logistic regressions remain a standard benchmark. For the purpose of this study, a number of calculations will be carried out including:

$$R_i = \frac{P_t - P_{t-1}}{P_{t-1}} \qquad (2)$$

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2} \qquad (3)$$

$$\alpha_i = E(R_i) - \beta_i \, . E(R_m) \qquad (4)$$

$$\sigma^2 = \sum_{i=1}^{n} \frac{(R_{it} - E(R_i))^2}{n} \qquad (5)$$

$$MoM = \frac{(\text{Small High} + \text{Big High})}{2} - \frac{(\text{Small Low} + \text{Big Low})}{2} \qquad (6)$$

where R_i represents the monthly stock return and is calculated by calculating the change of today's price (P_t) relative to yesterday's price (P_{t-1}). β_i measures the level of market risk for each stock and is estimated by finding the proportion of firm specific risk (σ_{im}) relative to the market risk (σ_m^2). Alpha (α_i) is estimated by the taking the difference between the expected return from the capital asset pricing model $E(R_i)$ and a market risk adjusted return ($\beta_i \, . E(R_m)$). Total risk is estimated by taking the average of the sum of squared deviations of the monthly returns from the expected returns. Similar to Dirk & Peter (2020) who adapted Fama & French (2015) measure of momentum, MoM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Six value-weight portfolios are formed on size and prior (2-12) returns to construct MoM. The monthly portfolios which are formed are the intersections of 2 portfolios formed on size (market equity) and 3 portfolios formed on prior (2-12) returns. The monthly size breakpoint is the median JCI market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th JCI percentiles. To be included in a portfolio for month t (formed at the end of month $(t-1)$), a stock must have a price for the end of month $(t-13)$ and a positive return for $(t-2)$. Stocks are classified as Small and Big based on size sorts, and High and Low based on book-to-market values.

Research models in the form of Variables Beta, Alpha, VAR, and Momentum as follows:

$$R_i = \frac{e^{(\beta 0 + \beta x1 + \beta x2 + \beta x3 + \beta x4)}}{1+e^{(\beta 0 + \beta x1 + \beta x2 + \beta x3 + \beta x4)}} \qquad (7)$$

The value of e is an exponential of the variable used, if the power of e is 1 then it indicates that the return of the stock exceeds the market return and if it is 0 then the stock's return is below the market return as a benchmark. The value of e is no more than the predictive contribution of the 4 variables used in this study. It is expected that models that can produce prediction accuracy that is close to actuals, as reflected in high per cent predictions, suggest more reliability in predicting stock returns. The determination of the acceptance or rejection of the hypothesis will be determined from the value of significance. The hypotheses that being tested will be given bellow:

H1: Beta affects the prediction of stock return, $H_1 = rejected,\ if\ Sig.value < alpha\ 0.05 = rejected$

H2: Alpha affects the prediction of stock returns $H_2 = rejected,\ if\ Sig.value < alpha\ 0.05 = rejected$

H3: Total risk affects the prediction of stock returns. $H_3 = rejected,\ if\ Sig.value < alpha\ 0.05 = rejected$

H4: MoM affects the prediction of stock returns. $H_4 = rejected,\ if\ Sig.value < alpha\ 0.05 = rejected$

IV. RESULT/FINDING

Dependent variables consist of 40,948 stock returns, where returns are grouped into binary codes 1 and 0. Specifically, 1 is a group of shares that have a return above the market from the data used. As per table 1, these represent 19,855 of data or 48.49 per cent with returns above the market. The group with binary values of 0 contains returns which are below the market represent 21,092 or 51.51 per cent of the selected data. The data that is used here is the whole population, such the data is heterogeneous. The effects of heterogeneity will result in bias in making investments and can lead to losses due to the bias in the data, such that the decision will be not accurate. Therefore, after we find out which stocks are biased, data outlets will be categorized into groups and premium stocks will be selected in forming the portfolio.

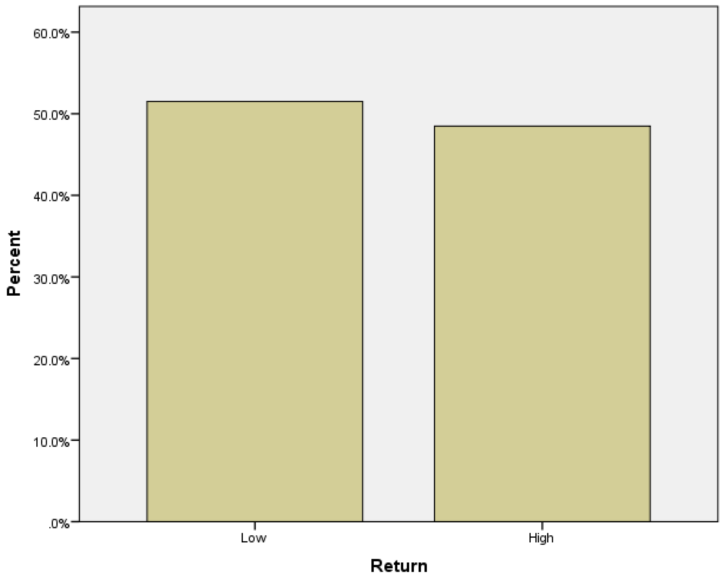

Figure 1. Classification of Return (Low and High)

Figure 1 represents 40,948 stock returns, where returns are grouped into binary codes 1 and 0. 1 is a group of shares that have a return above the market. The group with binary values of 0 contains returns which are below the market. These are represented as Low and High in Figure 1.

Beta values are found by estimating the slope between stock return and the Jakarta Stock Exchange Composite Index (JCI). Findings support that there is one data that has a maximum beta value of 33.2 and a minimum of -26.75 with an average of -0.036. This result means that there are stocks in a given period that have both positive outler prices that can result in the maximum positive beta value, and negative price movements that result in a maximum negative value. This scenario is not ideal since many biases will occur if investors choose the stock. Since price movements are too high, both positive and negative, this can potentially result in a high risk of losses. Therefore, investors are expected to be wary of stocks that have too high beta values. The average value of the negative beta is due to the majority of the data experiencing a below-market return as evidenced earlier in Figure 1, which led to this relationship between the market and individual stocks. This result also suggests that if the market moves positively then the data used responds negatively to the situation. This also happens because there is too much heterogeneous data used.

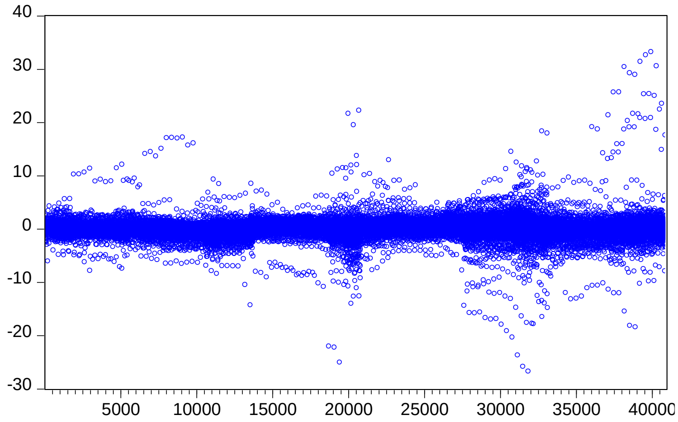

Figure 2. Beta

Figure 2 displays the beta values of monthly stock returns from 2009 to 2019 based on 353 stock samples in Indonesia. Beta values are found by estimating the slope between stock returns and combined Stock Price Index (JCI).

Figure 3 displays the behavior of Alpha values, with a maximum value of 0.848, a minimum value of -0.198 and an average value of 0.0182. Alpha values were obtained from intercept between the return of individual shares to the JCI market. A higher positive alpha value for a stock will yield a positive return beyond the return obtained by the market, and vice versa. Resultingly, investors can choose a group of stocks with premium returns quickly. However, the situation will be biased because the beta value only displays a return on a specific day without guarantee that the stock is premium (blue chip). Although the beta average value in Figure 2 is negative, and in Figure 1 the majority of the data gets a negative return, the average value of this heterogeneous data gets a positive result of 0.0182. This result means that the minority of stock groups with binary code 1 still get a positive average cumulative value. This is where the advantages of portfolio theory, where a well-diversified portfolio will not reduce the return of the portfolio, but the portfolio risk can be minimized if the data is filtered before being included in the portfolio. Therefore, as part of an effective step in the portfolio management process, a portfolio model that can anticipate a proper stock selection process is warranted. This will enable a diversified portfolio that can reduce risk while not sacrificing its return. As part of the stock selection process, individual asset risk becomes critical.

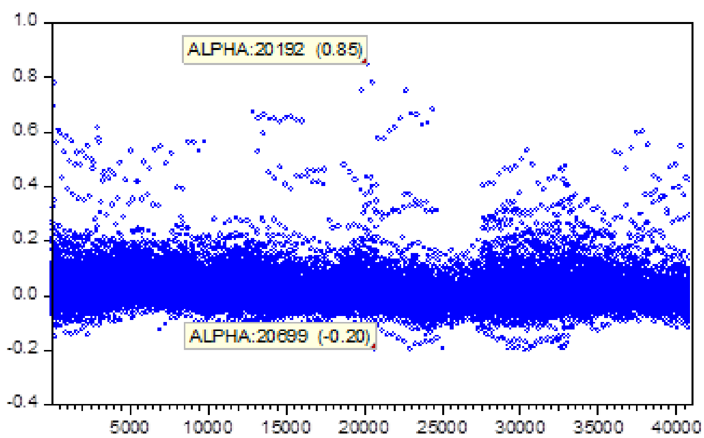

Figure 3. Alpha

Figure 3 displays the alpha values of monthly stock returns from 2009 to 2019 based on 353 stock samples in Indonesia. Beta values are found by estimating the intercept between stock returns and combined Stock Price Index (JCI).

Individual risk is obtained by calculating its VAR from the return data over the period of study. This resulted in a maximum VAR value of 5.1, a minimum value of 0, with an average value of 0.036. Risk is not negative because in accordance with the wise adage that "there is no free lunch" the maximum value of 5.1 does not necessarily mean that the stock has a positive return. This is because the VAR value is the absolute value of the return movement at a certain time, which can be both positive and negative. The value of VAR reflects a volatile level of price that impacts the return of the stock. High levels of fluctuation indicate that for high-risk stocks, investors need to be wary. If investors have the affinity to take the risk, then high fluctuation stocks become an option to buy and hold in a relatively short term or short time investment.

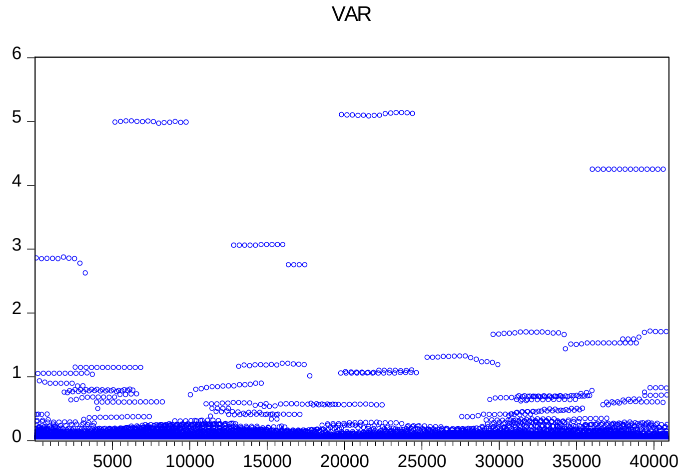

Figure 4. VAR

Figure 4 displays the total risk (VAR) of monthly stock returns from 2009 to 2019 based on 353 stock samples in Indonesia. VAR is estimated by taking the average of the sum of the squared deviation of the monthly returns from their averages.

MoM data is generated from historical data from the previous 12 months so that the amount of opportunity from future stock price movements is obtained. The maximum value of MoM data in this study is 100 per cent, minimum data is 0 per cent, and the average MoM data is 47.6 per cent. The value of 100 per cent in MoM means that there is a group of stocks that get a 100 per cent positive return on price movements that occur in the 12-month period, and there is data that has zero per cent where the stock has no chance to rise, since the price has not moved in the last 12 months. The average value of MoM obtained was 47.6 per cent, suggesting that there is a need to get a positive return for the next period. It is recommended for investors to choose a group of stocks that have a MoM value of more than 50.1 in order to get a positive return opportunity for the next period. While no one can be sure of the next price movement, investors can anticipate the risks that will occur by not carelessly choosing stocks, by considering MoM factors and factors that can describe the return and risk on the targeted stock.

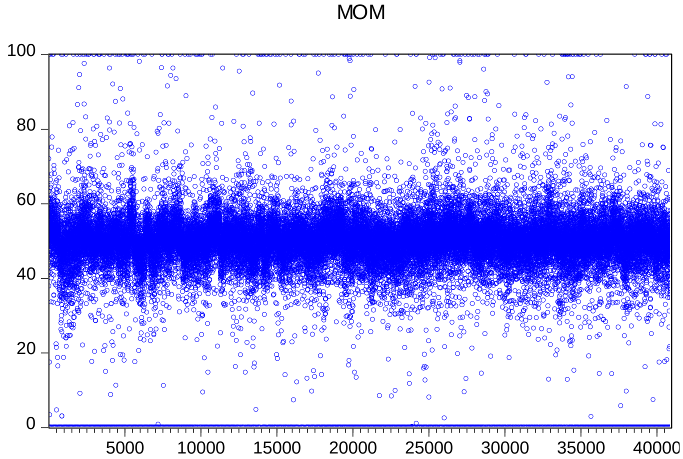

Figure 5. MoM

Figure 5 displays the momentum values of monthly stock returns from 2009 to 2019 based on 353 stock samples in Indonesia. MoM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Six value-weight portfolios are formed on size and prior (2-12) returns to construct MoM. The monthly portfolios which are formed are the intersections of 2 portfolios formed on size (market equity) and 3 portfolios formed on prior (2-12) returns. The monthly size breakpoint is the median JCI market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th JCI percentiles. To be included in a portfolio for month t (formed at the end of month *t-1*), a stock must have a price for the end of month (*t-13)* and a good return for (*t-2).*

Prediction Model Testing

Model testing in this study uses Logistic regression as depicted in Equation 1. In Table 1, the initial calculation of tabulation data, where the data group that generates below-market returns amounted to 21093 with code 0, and the stock group with a return above the market was 19855. If it is accumulated, then the number of sample tabulation data amounted to 40948. The initial prediction rate of the data tabulation results before entering the independent variable is 51.5 per cent. A good model is one that produces a higher predicted rate than before the entry of independent variables into the model.

Table 1. Early Model Predictions

			Predicted		
			RETURN		
	Observed		.00	1.00	Percentage Correct
Step 0	RETURN	.00	21093	0	100.0
		1.00	19855	0	.0
	Overall Percentage				51.5

The results of predictions after the entry of independent variables into the model produce a better prediction rate than before. The results obtained after entering the variable into the model amounted to 85.6 compared to the previous score of 51.5, representing an improvement of 34.1. The results support that there is an improvement in prediction results with the inclusion of independent variables consisting of Beta, Alpha, VAR, and MoM into the model for stock return prediction in Indonesia as per Table 2.

Table 2. Final Model Predictions

	Observed	Predicted

			RETURN		
			.00	1.00	Percentage Correct
Step 1	RETURN	.00	18915	2178	89.7
		1.00	3710	16145	81.3
	Overall Percentage				85.6

Logistics regression can detect the degree of error or incompatibility of the value of each variable independent of the category of dependent variables. For example, with the results of running data, logistic regression with the composition of independent variables gets a value with category 1, but the initial data with category 0. Furthermore, there is a misunderstanding of the results of data tabulation where if it is calculated from the value of each independent variable then the return of the stock gets a return above the market with category 1 of 2,178, so that the data that gets a return below the market with category 0 becomes 18,915 data. Furthermore, the stock return group above the market yielded an error of return, where the amount of data that got a return below the market amounted to 3,710, and the amount of data that had a return above the market to as much as 16,145 data.

Table 3. Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	BETA	.886	.019	2292.445	1	.000	2.427
	ALPHA	92.725	1.027	8151.454	1	.000	1.861E+40
	VAR	13.465	.950	200.777	1	.000	704220.052
	MoM	-.008	.001	68.250	1	.000	.992
	Constant	-.813	.045	332.926	1	.000	.443

Note: The variable entered on step 1 of Table 3 are BETA, ALPHA, VAR andMoM. BETA measures the level of market risk for each stock and is estimated by finding the proportion of firm specific risk relative to the market risk. Alpha is estimated by the taking the difference between the expected return from the capital asset pricing model and a market risk adjusted return. Total risk is estimated by taking the average of the sum of squared deviations of the monthly returns from the expected returns. MoM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

Based on Table 3, the results suggest that beta variables have a significant effect on the prediction of stock return in Indonesia. Hypothesis 1 is accepted with a significant coefficient value of 0.886. The positive direction of the influence of variable beta stock prediction in Indonesia is indicated by the value of wald. Furthermore, the alpha variables have a significant influence and has a positive influence direction on the prediction of stock returns in Indonesia so that hypothesis 2 is accepted, with a coefficient value of 92,725. The total risk (VAR) variable has a significant effect on the prediction of stock returns in Indonesia with a positive influence direction with a coefficient value of 13,456 thus hypothesis 3 is also accepted. Momentum variables (MoM) have a significant influence, have a positive influence direction shown by the value of wald, with a coefficient value of -0.008, (Hypothesis 4 is accepted)

Table 4. Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	28697.202[a]	.496	.661

Note: [a] Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

As per table 4, the prediction model with beta, alpha, VAR and MoM variables captured in the study has an adjusted Cox & Snell r-squared value of 0.661 which can explain how the prediction of return of shares in

Indonesia, with the remaining 33.9 per cent explained by external factors not captured by our variables. Importantly, bias and the abundance of information in the market is the biggest problem in portfolio formation. Therefore, portfolio formation returns to the investor's knowledge of methods, models and trail errors in portfolio design that are in accordance with the appropriate risks that investors can tolerate. This research supports the finding of Bender *et al.* (2019) that portfolios are formed on the basis of investors' structure, established metrics, and adjustment of industrial and state types in terms of empirical choice.

Beracha & Downs (2015) studied that the value and momentum factors are used for the measurement of returns and risks in real estate investments, each of which was correlated with macroeconomic factors that vary and are different. The value factors are strong when the real estate market weakens, and momentum factors occur in economic conditions that are experiencing strong growth. Based on the results of the study, it can be concluded that the value and momentum factors have their respective functions under certain economic conditions. Similarly, research suggest that beta, alpha, total risk, and momentum variables have different functions under certain conditions.

V. DISCUSSION

The analysis of the result focuses on the prediction of stock returns in Indonesia using a logistic regression model. This incorporates various independent variables such as Beta, Alpha, Var and MoM to predict the likelihood of stock returns. We can see that the initial prediction rate of the data tabulation results before entering the independent variables is 51.5%. Then after entering the variables into the model, the prediction rate improves to 85.6% representing an improvement of 34.1%. This indicates that the model is effective in predicting stock returns and can be used as part of the portfolio management process. Logistics regression can detect the degree of error or incompatibility of the value of each variable independent of the category of dependent variables. For example, with the results of running data, logistic regression with the composition of independent variables gets a value with category 1, but the initial data with category 0. This makes more accuracy on building the momentum strategy to have an improvement for having return and reducing the risk.

This research shows that it has implications for investment strategy in Indonesia, particularly during episodes of downturn. Investors can take advantage of the momentum of high volatility to obtain a premium return. It is also suggested that portfolio should be firmed based on investors structure, established metrics and adjustment of industrial and state types. This also concludes that the developed model can effectively predict stock returns in the Indonesian stock market. By considering momentum factors along with beta, alpha and total risk, Investors can make informed decisions on when to buy and sell investments. The model offers a practical approach to investment strategy in Indonesia. On the other side it is also recommended that investor consider the momentum of high volatility in emerging markets and actively manage their investments to reduce losses caused by a decrease in asset performance.

VI. CONCLUSION AND RECOMMENDATION

Emerging market economies are characterized by high levels of fluctuations in stock prices/ high volatility. Investors can take advantage of the momentum of high volatility to get a premium return. Return premium can be obtained by utilizing models from previous research that can be applied practically. This study offers a practical model and an accuracy rate of 85.6 per cent to predict stock returns with Beta, Alpha, VAR, and MoM variables that affect the prediction of stock returns on the Indonesian stock exchange. The variables used can explain the prediction of return in Indonesia of 66.1 per cent and the rest is explained beyond the variables studied. The amount of accuracy and explanation of the variables used is not a problem, since the main factors needed in portfolio design are consistent, disciplined and how investors are able to apply the model for portfolio design in their investments. After the model is constructed, a portfolio can be formed and actively managed in Indonesia, as seen in Salim *et al.* (2020) and Hendrawan *et al.* (2021). Future portfolio design developments will use artificial intelligence that has been input by a number of models from research results that can study the state of asset prices in real time. More specifically, as reviewed in Gurrib (2022), machine learning has a critical role to play in portfolio management. The use of machine learning will facilitate the decision-making process with respect to the assets to be included in the portfolio. Investors in the future only needs to determine their willingness to accept investment risk, which funds to invest, and which group of assets to invest. Following these inputs from the investor, the system will run automatically choosing assets that are in accordance with the will of the investor. Future researchers are advised to combine a number of types of investment instruments into one and create a more accurate predictive model of the study. The model used in the study is based on logistic regression, which can be extended to other algorithms such as random forests, long-short term memory, linear discriminant analysis, artificial neural networks, among others, to find the determinants of stocks returns in emerging and non-emerging economies. This type of modeling will facilitate the creation of a more robust system to benefit of investment clients.

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