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STOCK PORTFOLIO OPTIMIZATION IN BULLISH AND BEARISH CONDITIONS USING THE BLACK-LITTERMAN MODEL

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Abstract

Bullish and bearish phenomena characterize the development of the capital market. Therefore, this study aimed to identify and analyze bullish and bearish conditions in the Indonesian capital market to formulate an optimal portfolio. The sample consisted of 20 selected companies based on their substantial market capitalization. The results showed that from January 2011 to December 2020, the capital market experienced 77 bullish and 43 bearish months. The transition probability from bullish to bearish and bearish to bullish state was 15.67% and 56.14%. Furthermore, employing the Markov-switching model for determining market conditions and using the Black-Litterman model for portfolio construction proved advantageous for investors' financial forecasting techniques and their potential to generate valuable insights to create a well-informed portfolio.

Keywords: Bullish and bearish, optimal portfolio, Black-Litterman model.

Introduction

Changes in market conditions are frequently observed within the capital market dynamics. However, it is imperative to consider various implications due to the potential disparities in an investment's expected return and risk caused by bullish and bearish cycles. Investors prefer returns while actively evading risk and may allocate their investments towards more precarious assets for a higher expected return (Brigham & Houston, 2009). Empirical facts also show that the variables have a positive correlation, meaning investors must take more significant risks to obtain higher returns.

Diversification can reduce risk by combining different investment instruments into a portfolio. The discipline of portfolio management involves selecting and managing assets corresponding to an investor's long-term financial objectives and willingness to take risks (Mourtas & Katsikis, 2022). By selecting assets, a well-constructed portfolio can balance and mitigate the risks and returns associated with each asset, resulting in an overall performance that surpasses the assets when considered independently. Investment portfolios are formed using a combination of diverse or a blend of assets and risk-free assets within the capital market (Maulana, 2020).

Harry Markowitz introduced portfolio theory in 1952 in the article "Portfolio Selection." The Markowitz portfolio theory is modern (Ivanova & Dospatliev, 2017). Markowitz proposes the theory of forming the mean-variance optimal portfolio by creating a portfolio selection model that incorporates the principle of diversification (Shahid, 2019).

In the mid-1960s, William Sharpe, John Lintner, and Jan Mossin introduced the Capital Asset Pricing Model (CAPM) concept. CAPM is utilized as a balancing model that combines the expected return of a risky asset with the risk-free rate within the framework of balanced market assumptions (Sholehah, Permadhy, & Yetty, 2020). It can assist investors in calculating the non-diversified risk of a portfolio as measured by beta (Dinahastuti, Badruzaman, & Wursan, 2019).

One of the challenges in making decisions regarding financial management, such as portfolio investment, is incorporating quantitative and judgmental perspectives from investors. Concerning the weakness of the Markowitz and CAPM model, investors' views of the assets should be considered. Opinions can be provided by looking at stock price movements about changes in market conditions and their effect on fluctuations (Subekti, 2009).

To overcome this weakness, in the 1990s, Fisher Black and Robert Litterman introduced the Black-Litterman asset allocation model, which combines two types of information, namely expected equilibrium returns and investor views (Andrei & Hsu, 2020). This method strives to resolve issues linked to the non-intuitive and excessively focused portfolio and the sensitivity to input in the Markowitz model (Wutsqa, Pamungkas, & Subekti, 2021).

The Black-Litterman model's primary innovation is its fusion of the Markowitz model, the CAPM market equilibrium, and the Bayesian method. From a practical perspective, this method offers portfolio managers a systematic means of expressing subjective viewpoints, liberating their investment methods from relying on past historical data (Kolm, Ritter, & Simonian, 2021). This amalgamation offers investors a potent means of computing optimal portfolio weights as a favored model among portfolio investment managers (Ta & Vuong, 2020).

The Black-Litterman model produces more stable and accurate return estimates with lower risk than the Markowitz. Therefore, the model performs better in optimizing stock portfolios (Bessler, Opfer, & Wolff, 2014). Mahmuda and Subekti (2017), Izzati, Sulistianingsih, and Wira (2019), and Murtadina, Saputro, and Utomo (2021) showed that the portfolio formed from the Black-Litterman model produced better and more profitable performance compared to the benchmark portfolio, namely CAPM. The Black-Litterman model can identify disparities between the estimate of the CAPM and the actual returns based on historical data, comprehend the conduct of biased investors, and adjust the portfolio accordingly (Chen & Lim, 2020). In addition, investors tend to find portfolio structure more agreeable because of the greater level of diversification (Stoilov, Stoilova, & Vladimirov, 2022).

The Black-Litterman model uses the Bayesian framework to incorporate investor views into the asset allocation process effectively. The Bayesian framework uses the equilibrium return estimated through the CAPM to produce a new view of return expectation (as a posterior distribution). To achieve optimal benefits from the asset allocation model, investors must determine the combination of single and multiple views.

The Black-Litterman model relies on a single scalar uncertainty parameter τ to define uncertainty about the equilibrium returns. However, this method has limitations, which can pose challenges in the application and potentially violate a significant theoretical assumption of the model. The choice of τ significantly impacts the final allocation and implicitly predetermines the asset allocation since the subjective se-lection of τ is crucial (Fuhrer & Hock, 2023). Mahrivandi, Noviyanti, and Setyanto (2017) indicated that a higher confi-dence level of investor views (τ) led to a higher target return and increased risk level.

The Black-Litterman asset allocation model faces two significant issues. The first issue is its reliance on the assumption of multivariate normality for the market prior and investor views on asset returns, as well as the challenge of estimating parameters for the non-normal distribution of the market in the Bayesian framework (Meucci, 2006).

The second issue is the failure to consider the changing volatility regimes. Instead of relying on historical volatility, the method computes the covariance matrix of excess returns by giving equal weights to the entire historical period. Therefore, the computed efficient allocation may differ significantly from the accurate efficient allocation, leading to unnecessary transaction costs due to high portfolio turnover and inefficiencies in capital allocation (Huuhka, 2022). The problem is selected to be addressed because it aligns with De la Torre-Torres, Galeana-Figueroa, Del Río-Rama, and Álvarez-García (2022) and Oprisor and Kwon (2020) study, bearing the closest resemblance to this method.

This model also highlights carefully the process of generating or acquiring the viewpoint vector due to financial markets' intricate and evolving nature. Various studies emphasize the challenge of creating investor views within Black-Litterman modeling and strive to use diverse forecasting methods, such as historical return records or indicators, to generate more precise or unbiased investor views (Kara, Ulucan, & Atici, 2019).

Time-series analysis can form investor views in the Black-Litterman model (Su, Kek, Asrul, & Abdullah, 2019). Numerous time series techniques exist to generate the viewpoints of investors. Min, Dong, Liu, and Kong (2021) employed machine learning algorithms to minimize the generalization error. Ta and Vuong (2020) utilized the ARIMA method, while Mahrivandi *et al.* (2017) and Arisena, Noviyanti, and Soleh (2018) used the ARIMA-GARCH method to overcome the heteroscedasticity problem in modeling volatility. A Markov-Switching component was introduced to enhance the responsiveness of the Black-Litterman model to changes in the market regime and reduce the level of effort required for interaction.

Markov-Switching model offers certain advantages, such as calculating mean and standard deviation parameters for various states or regimes. From behavioral finance and security analysis, a regime refers to a low (bullish) or high volatility (bearish) period. Furthermore, these models help forecast the likelihood of each regime and enable its anticipation. The estimated parameters were used to project portfolio performance in a multi-regime scenario, allowing them to make informed investment decisions (De la Torre-Torres *et al.*, 2022).

Various studies regarding the implementation of the Black-Litterman model in the formation of optimal portfolios have been carried out by Mahrivandi *et al.* (2017), Arisena *et al.* (2018), Izzati *et al*. (2019), Pudjiani, Syaukat, and Irawan (2020), and Murtadina *et al*. (2021), where bullish and bearish condition in the capital market was not considered. The compo-sition of the shares in the portfolio needs to be adjusted to produce a trade-off between optimal return and risk following preferences when conditions change. By forming a different portfolio in bullish and bearish conditions, investors can obtain optimal returns and are better prepared to face risks due to changes.

This study is driven by the desire to address these issues, and its objective is to explore and implement an integrated strategic asset allocation model that combines the Black-Litterman model with the ability to switch between bullish and bearish volatility regimes. Combining these two methods can improve covariance estimation without compromising investor views. Moreover, identifying changes in bullish and bearish market volatility regimes can give investors a greater understanding of market dynamics, influencing their decisions and improving expected returns on various assets.

Bullish and Bearish Condition

Price movement in the stock market can be tracked using the average price and market indices. At any given moment, the average price movement signifies the price behavior of a representative set of shares. Meanwhile, the market index contrasts the present value of a representative group of share prices with the price during the base period. The average price or index's upward and downward trajectory is considered bullish and bearish, respectively (Tambunan, 2020). Bullish derives from the word bull, which represents an upward movement. This term symbolizes market participants' optimism toward rising prices.

Conversely, bearish stems from the word bear, which signifies a downward movement. This term represents market participants' pessimism regarding falling prices, as visualized by a bear swinging its paw down. Fabozzi and Francis (1979) classified bullish and bearish markets based on their level of returns. Furthermore, when the market's return level is positive during a specific period, it is considered bullish; when negative, it is classified as bearish.

CAPM

CAPM is a portfolio optimization model that correlates the expected return of a risky asset with the other type of market in equilibrium or assumptions (Tandelilin, 2017). The concept assumes that investors hold a well-diversified portfolio and that only systematic risk is relevant. Systematic risk refers to the sensitivity of an asset to economic factors affecting a financial asset. Therefore, diversification can only partially eliminate systematic risk, and investors will demand a premium for investing in risky assets. The systematic risk of an asset is directly proportional to the required return (Megginson, 1997). Furthermore, CAPM can be expressed in the following equation:

$$E(R_i) = R_f + \beta_i\big(E(R_M) - R_f\big)\,;\, i = 1{,}2, \ldots, n$$

The time-varying market risk model is used with the following equation (Tandelilin, 2001) to estimate stock beta in bullish and bearish conditions:

$$\begin{aligned} R_t = \alpha_{bull} + (\alpha_{bear} - \alpha_{bull})D + \beta_{bull}R_{Mt} \\ + (\beta_{bear} - \beta_{bull})R_{Mt}D + \varepsilon_t \end{aligned}$$

Remarks:

$E(R_i)$: The expected return of stock *i.*
$E(R_M)$: The expected return of the market index.
R_f : The return of the risk-free asset.
β_i : Systematic risk of stock *i.*
R_t : The stock return of month *t.*
R_{Mt} : The market return of month *t.*
α_{bull} : Abnormal return in a bullish condition.
α_{bear} : Abnormal return in a bearish condition.
β_{bull} : Beta in a bullish condition.
β_{bear} : Beta in a bearish condition.
D : Indicator variable (biner), 1 and 0 when the market is bullish and bearish.

Black-Litterman Model

The Black-Litterman model is a fundamental element of customary quantitative investing techniques with statistical analysis and modern optimization. This fundamental is because the model furnishes a meticulous and scalable structure to integrate historical data with subjective investors' stock views in their portfolios.

The Black-Litterman model is an updated version of Markowitz, particularly when updating the target expected return. The model merges the equilibrium return, calculated through the CAPM, with the forecasted return from the investor view (Subekti, Abdurakhman, & Rosadi, 2022). It relies on the historical covariance structure and considers the past relationships between asset returns to predict future behavior. Additionally, it assumes that the benchmark portfolio weights, determined based on market capitalization, are consistently in equilibrium (Martin & Sankaran, 2019).

The key innovation of the Black-Litterman model is introducing the notion of revising a portfolio based on investor perspectives. However, including viewpoints may introduce a subjective element to the modeling process (Kara *et al*., 2019). Model accomplishes this by utilizing equilibrium expected excess returns derived from observed market capitalization, which are the returns on assets required to maintain a balance between supply and demand for risk assets, as well as to counterbalance unreasonable large or small portfolio weights (Oprisor & Kwon, 2020; Barua & Sharma, 2022)

The main attribute of the Black-Litterman model is the assumption that the expected return is not an observable fixed value but a stochastic variable around the population average, normally distributed. The expected return must be modeled concerning the probability distribution in these circumstances. Meanwhile, actual returns are considered observable random variables derived from historical data (Olsson & Trollsten, 2018).

Investors can only view several assets from n the assets contained in the portfolio. Including different stocks in the portfolio necessitates the consideration of investors' viewpoints, which can be addressed by employing a diverse forecasting model. In addition, absolute and relative views are known in the Black-Litterman model. Investors have the opportunity to express their views on a portfolio comprising A, B, and C distinct shares (Ratri, 2015).

View 1 (*absolute view*)	:	"I believe asset A will give a *return* of *x*%."
View 2 (*relative view*)	:	"I believe that asset B will give a *return* of *y*% more than asset C."

The formula of the expected return from the Black-Litterman model is as follows:

$$\mu_{BL} = [(\tau\Sigma)^{-1} + P'\Omega P]^{-1}[(\tau\Sigma)^{-1}\pi + P'\Omega^{-1}Q]$$

The weight of the shares in the portfolio formed by the Black-Litterman model can be written mathematically as follows:

$$W_{BL} = (\delta\Sigma)^{-1}\mu_{BL}$$

The formula of the return (*Rp*) and risk ($\sigma^2 p$) of the Black-Litterman model portfolio is as follows:

$$R_p = W_{BL}{}'\mu_{BL}$$
$$\sigma_p^2 = W_{BL}{}'\Sigma W_{BL}$$

Remarks:

μBL : Expected return vector Black-Litterman model of $(p \times 1)$ size

τ : The level of investor confidence in his views

Σ : Covariance matrix of stock return of size $(p \times p)$

P : View the weight matrix of size $(q \times p)$

Ω : Investor's view uncertainty matrix $(q \times q)$

π : Return equilibrium vector of size $(p \times 1)$

Q : View $(q \times 1)$ return matrix.

W_{BL} : Vector of stock weights in the optimal portfolio of size $(p \times 1)$.

δ : Risk aversion coefficient.

R_p : Return portfolio Black-Litterman.

σ_p^2 : Black-Litterman portfolio return variance.

Research Methods

Data and Sample

This study uses data on monthly stock or adjusted closed prices from January 2011 to December 2020 obtained from the website https://finance.yahoo.com. The proxy for the market index is the JCI obtained from the website https://finance.yahoo.com and the proxy for risk-free assets are the Indonesia Government Bond 10-year obtained from the website https://id. investing. com. Government bonds are debt securities issued and guaranteed by the Indonesian government for financing. Meanwhile, the issuance scheme of government bonds involves offering them to individuals, and the bond system entails the repayment of debt accompanied by yield or coupon payments until maturity. This study uses a sample of 20 companies selected purposively based on the weight of the largest market capitalization in 2020.

Assumption Test

a. Structural Change Test

A change in structure occurs in time series data, and the regression model has parameter values that vary over time (Bai & Perron, 2003). Structural changes can be identified using a breakpoint test.

H_0: $\delta = 1$ (there is no structural change)

H_1: $\delta \neq 1$ (there is a structural change)

The test statistics used are:

$$F = \frac{\left(RSS_C - (RSS_1 + RSS_2)\right)/s}{(RSS_1 + RSS_2)/(T - 2s)}$$

Remarks:

RSS_C : The sum of squares of the residuals of the regression model with all the data (T).

RSS_1 : The sum of the squares of the regression model residuals before the break occurs.

RSS_2 : The sum of the squares of model residuals after the break occurs.
S : The number of parameters to be estimated.

Test criteria: reject H_0 if F Chow is greater than $F_{(s,T-2s)}$, or *p-value* < α, and accept otherwise.

b. Stationarity Test

Stationarity is a condition where time series data's mean, variance, and covariance do not change over time (Makridakis, Wheelwright, & McGee, 1993). The unit root test is one of the formal concepts used to test data stationarity. Furthermore, David Dickey and Wayne Fuller created the Augmented Dickey-Fuller (ADF) test.

H_0 : $\beta = 1$ (data is not stationer)
H_1 : $|\beta| < 1$ (data is stationer)

The test statistics used are:

$$t_\beta = \frac{\hat{\beta}_1 - 1}{SE(\hat{\beta}_1)}$$

Test criteria: reject H_0 if $|t_\beta|$*it* is greater than the Dickey-Fuller $(t_{n,\alpha})$ critical value or *p-value* < α, and accept in other respects.

Markov-Switching Regression

Markov-switching regression is a time series model used to model time series data that changes conditions. The basic concept of Markov-switching is to create a dynamic model as the data pattern changes. An unobserved discrete random variable influences this pattern change (S_t), known as the regime or state. The Markov-switching model is considered more comprehensive because it captures complex phenomena from the dynamics of changing data patterns. The Markov-switching model was formulated by Hamilton (1989) as follows:

$$Y_t = \mu_{S_t} + \varepsilon_t\ ,\ \ \varepsilon_t \sim N(0, \sigma^2_{S_t})$$

μ is a constant that depends on S_t, and in this study, S_t = 1 is the condition where the JCI is bullish, and S_t = 2 is the condition where the JCI is bearish. The Markov-switching model is equipped with transition probabilities from one state to another. The transition probability to model the change in condition is formulated based on the first-order Markov chain as follows:

$$P(S_t = j | S_{t-1} = i, S_{t-2} = k, \ldots) \\ = P(S_t = j | S_{t-1} = i) = p_{ij}$$

p_{ij} is the probability that the state *i* will be followed by the state j for $i, j \in \{1, 2\}$ with $0 \le p_{ij} \le 1$. Transition probability collections can be written as the transition probability matrix *P*:

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

Optimal Portfolio Formation

The steps for forming an optimal portfolio in bullish and bearish conditions are as follows:

a. Calculating stock returns and risks.

Return is the rate of return on investment as a return on investors' funds. Furthermore, the possibility of deviation between the actual and the expected return is called risk. The formula for calculating the return and risk of individual stock is as follows:

$$R_i = ln\left(\frac{P_t}{P_{t-1}}\right)\ \ and\ \sigma_i = \sqrt{\frac{\sum_{i=1}^{n}(R_i - E(R_i))^2}{n-1}}$$

Remarks:
R_{it} : Stock return *i*.
P_t : Closing price in month *t*.
P_{t-1}: Closing price in month $t-1$.
σ_i : Standard deviation of stock return *i*.
n : Number of observations.

b. Stock beta (β) and expected return CAPM (π) vector are estimated and calculated.
c. The candidate stock forming portfolio based on significant beta and the positive expected return obtained in step b was determined.
d. Shaping the views of investors and the proposal involves using a Markov-switching technique to anticipate stock returns, which are then used as vectors for investor views in Black-Litterman modeling to establish a portfolio. The proposed model is evaluated in a bullish and bearish market scenario.
e. Determine the view weight matrix (*P*), the view return matrix (*Q*), and the investor view uncertainty matrix Ω.
f. The expected return vector of Black-Litterman (μ_{BL}) and the vector of stock proportions (W_{BL}) were also calculated for portfolio return and risk.

Results and Discussion

JCI Overview

Stock prices are formed because of demand and supply. According to the law of supply and demand, stock prices will rise when demand is greater than supply.

The equilibrium price in the capital market will be reached when there is a meeting of the price offered by the seller and the price asked by the buyer. The movement of the JCI provides an overview of the performance of the capital market, and it is used as a reference for statistical analysis of current market conditions.

Figure 1 reflects the formation of stock prices in the capital market. The JCI curve tends to rise, indicating that stocks in the capital market have high buying pressure. Meanwhile, the JCI curve tends to fall, indicating that many investors are willing to sell their shares.

The JCI reached its lowest and highest value in January 2011 (3,049.167) and 2018 (6,605.631). The average JCI during the observation period was 5,074.248, with a standard deviation of 834.375.

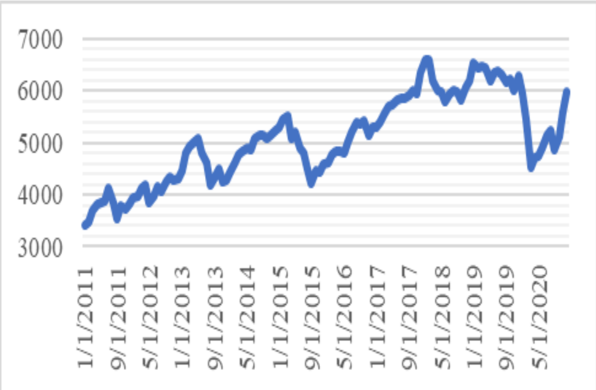

Figure 1. JCI curve 2011–2020

The JCI has strengthened several times, as indicated by a positive performance record, namely in 2011 (3.20%), 2012 (12.94%), 2014 (22.29%), 2016 (15.32%), 2017 (19.99%), and 2019 (1.70%). However, the JCI has also weakened several times, marked by a negative performance record, namely in 2013 (-0.98%), 2015 (-12.13%), 2018 (-2.54%), and 2020 (-5.09%). The strengthening and weakening of the JCI are referred to as bullish and bearish.

Assumption Test

a. Structural Change Test

Structural changes in the JCI data were identified using a breakpoint test with the following results (Table 1).

Table 1
Structural Change Test

Chow Breakpoint Test	
Sup{F}	*p-value*
181.41	< 2.2*e*-16

The breakpoint test with the F Chow statistic resulted in a *p-value* < 2.2*e*-16, smaller than the significance level α = 5%. It can be concluded that the JCI data were subjected to a structural change.

b. Stationarity Test

The stationarity test on the JCI data was used to determine the stability of the capital market. Stationarity was tested using the ADF test with the following results in Table 2.

Table 2
JCI Stationarity

Dickey-Fuller Stats	Lag Order	*p-value*
-2.7488	4	0.2656

The JCI stationarity test resulted in a *p-value* = 0.2656, greater than the significance level α = 5%. It can be concluded that the JCI data was not stationary and was necessary to transform from index to return data to obtain stationary data. Testing the stationarity of JCI returns produces the following output of Table 3.

Table 3
Stationarity of JCI Returns

Dickey-Fuller Stats	Lag Order	*p-value*
-5.0987	4	0.0100

Testing the stationarity of JCI returns yields a *p-value* = 0.0100, which is smaller than the significance level α = 5%. It can be concluded that the JCI return data is stationary. Therefore, the stability of the Indonesian capital market cannot be observed directly based on the JCI but can be seen significantly based on its return.

JCI Modelling

Based on the assumption test, the JCI data were subjected to a stationary structure change in its return. Therefore, the JCI modeling must use a time series model, showing the dynamic pattern over different periods.

JCI was modeled using Markov-switching regression. According to Hamilton (1989), the parameter estimation of the Markov-switching model is carried out using the maximum likelihood method combined with filtering and smoothing algorithms.

Based on Table 4, the Markov-switching model formed is

$$\mu_{S_t} = \begin{cases} 0.0203, & S_t = 1\ (Bullish) \\ -0.0549, & S_t = 2\ (Bearish) \end{cases}$$

and

$$\sigma^2_{S_t} = \begin{cases} 2 \times 10^{-8}, & S_t = 1\ (Bullish) \\ 6 \times 10^{-8}, & S_t = 2\ (Bearish) \end{cases}$$

Table 4
Markov-Switching Model Parameter Estimates

Regime	Parameter Estimate	Coefficient	Standard Residual	*z-statistics*	*p-value*
Bullish	$\hat{\mu}_1$	0.0203	0.0033	6.1885	0.0000
	$\hat{\sigma}_1$	0.0002	0.0262	-2.0969	0.0360
Bearish	$\hat{\mu}_2$	-0.0549	0.0998	-37.4118	0.0000
	$\hat{\sigma}_2$	0.0006	0.3772	-8.4519	0.0000

JCI produces an average positive return of 2.03% per month in bullish conditions, equivalent to 24.36% of profit per year. In bearish conditions, JCI produces an average negative return of -5.49% per month, equivalent to a 65.88% yearly loss.

The standard deviation at bullish and bearish times is 0.02% and 0.06%, respectively. This value means that bullish conditions have lower volatility than bearish conditions.

This volatility indicates that differences in returns and volatility cause changes in market conditions. Therefore, bullish conditions are defined as positive returns with low volatility (low risk), while bearish conditions are defined as negative returns with high volatility (high risk).

Bullish and Bearish Condition Identification

a. Transition Probability and Expected Duration
The transition probability matrix contains the values for bullish and bearish conditions and the probability of moving from bullish to bearish conditions. The probability of transitioning between bullish and bearish conditions is shown in Table 5.

Table 5
Transition Probability Matrix

	Bullish Condition	Bearish Condition
Bullish Condition	0.8433	0.1567
Bearish Condition	0.5614	0.4386

The probability that the capital market will remain bullish (84.33%) is greater than bearish (43.86%). In addition, the transition probability from bullish to bearish condition (15.76%) is smaller than bullish (56.14%). Therefore, the tendency of bullish conditions in the Indonesian capital market is stronger than the bearish condition. The capital market can maintain conditions to remain bullish when there is bullishness. In a bearish state, the capital market recovers quickly and becomes bullish again. In addition to the transition probability matrix, the Markov-switching model also provides information on the expected duration and the average duration of bullish and bearish conditions.

$$\text{Expected Duration Bullish} = \frac{1}{1-p_{11}}$$
$$= \frac{1}{1-0.8433} = 6.38 \text{ months}$$

$$\text{Expected Duration Bearish} = \frac{1}{1-p_{22}}$$
$$= \frac{1}{1-0.4386} = 1.78 \text{ months}$$

The calculation result shows that the bullish condition's expected duration is greater than the bearish condition. Therefore, the average bullish duration is longer than the average bearish duration (Figure 2).

b. Regime Distribution
To determine the timing of bullish and bearish occurrences in detail, it is necessary to detect them through a diagnostic plot. This plot provides information on the probability of each observation unit entering a bullish or bearish condition.

From January 2011 to December 2020, the Indonesian capital market experienced four bullish and bearish times. The complete summary of the periods is presented in Table 6.

From January 2011 to December 2020, the Indonesian capital market experienced 77 months (64.17%) and 43 months (35.83%) of bullish and bearish conditions. This value further reinforces the fact that the Indonesian capital market tends to be in bullish condition.

CAPM Portfolio

In the CAPM, the risk influencing the stock's expected return is the systematic risk measured by beta (β). The beta coefficient reflects the relative stock risk to the market portfolio. The beta coefficient is estimated using the time-varying market risk model in bullish and bearish conditions, and the results of the stock beta estimation are shown in Table 7.

CPIN (1.7809) and TPIA (0.1383) produced the largest and smallest stock beta in bullish conditions. In bearish condition, the largest and smallest beta of BBNI and SMMA was 2.3551 and -0.3774.

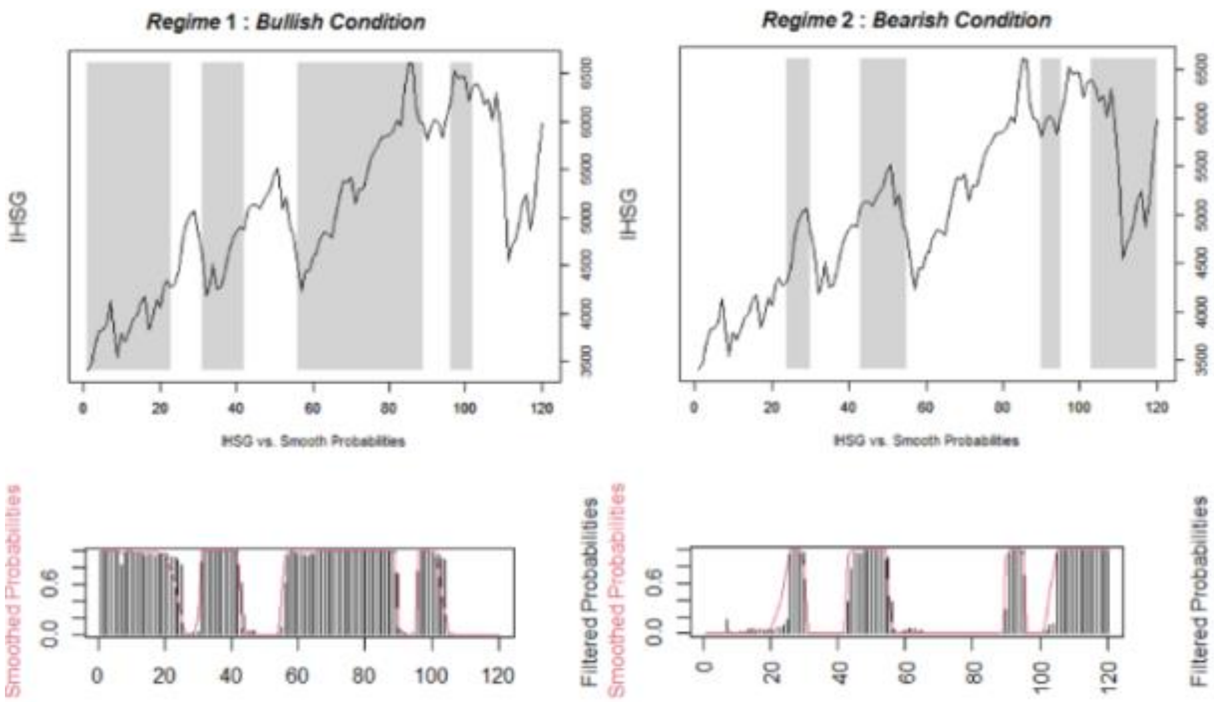

Figure 2. Diagnostic plot

Table 6
Bullish and Bearish Segmentation

Bullish Condition		**Bearish Condition**	
January 2011–November 2012	23 months	December 2012–June 2013	Seven months
July 2013–June 2014	12 months	July 2014–June 2015	12 months
July 2015–May 2018	35 months	June 2018–November 2018	Six months
December 2018–June 2019	Seven months	July 2019–December 2020	18 months
Total	77 months	Total	43 months
Percentage	64.17%	Percentage	35.83%

Table 7
Stock Beta in Bullish and Bearish Condition

Share	***β* Bullish**	***β* Bearish**	***F*-statistic**	***p-value***
BBCA	1.0420	0.9726	48.6336	0.0000
BBRI	1.5663	1.6070	65.1992	0.0000
TLKM	0.5534	0.7598	9.8727	0.0000
BMRI	1.5333	1.6808	84.0143	0.0000
UNVR	0.4220	0.1856	2.0845	0.1061
ASII	1.2482	1.5000	46.3178	0.0000
HMSP	0.9279	1.0528	14.6248	0.0000
TPIA	0.1383	1.2872	3.1239	0.0286
BBNI	1.5352	2.3551	79.0332	0.0000
ICBP	0.8572	0.4860	10.0277	0.0000
CPIN	1.7809	1.0125	15.9382	0.0000
BRPT	1.5362	1.2527	5.9031	0.0009
UNTR	1.1781	0.4126	10.0067	0.0000
BNLI	1.1996	1.2183	10.5775	0.0000
EMTK	0.6824	0.7642	3.4148	0.0198
GGRM	0.6995	0.8277	9.4254	0.0000
SMGR	1.5161	1.6478	38.6487	0.0000
SMMA	0.2286	-0.3774	0.6085	0.6108
KLBF	1.0288	0.7068	17.2900	0.0000
MYOR	0.7472	0.6497	5.7137	0.0011

Stock with a beta coefficient greater and less than 1 has a high and low sensitivity to market changes. Meanwhile, stocks with a negative beta coefficient indicate the movement of prices in the opposite direction of the market index. The *F*-statistic and *p*-value show the significant effect of systematic risk on the expected stock return in each market condition. In bullish or bearish conditions, UNVR and SMMA produce insignificant betas and are not involved in forming an optimal portfolio.

After obtaining a systematic risk estimate, each stock's expected return will be calculated using the CAPM formulation. Murtadina *et al.* (2021) reported that the optimum stock diversification consists of stock with positive π (the vector of expected return CAPM).

Table 8

Expected Return CAPM

Share	μ_{CAPM} Bullish	μ_{CAPM} Bearish
BBCA	0.0028	0.0034
BBRI	-0.0271	-0.0350
TLKM	0.0307	0.0163
BMRI	-0.0252	-0.0394
UNVR	0.0382	0.0511
ASII	-0.0089	-0.0285
HMSP	0.0093	-0.0014
TPIA	0.0544	-0.0156
BBNI	-0.0253	-0.0803
ICBP	0.0134	0.0329
CPIN	-0.0394	0.0010
BRPT	-0.0254	-0.0135
UNTR	-0.0049	0.0373
BNLI	-0.0058	-0.0114
EMTK	0.0234	0.0161
GGRM	0.0224	0.0122
SMGR	-0.0242	-0.0374
SMMA	0.0493	0.0852
KLBF	0.0039	0.0195
MYOR	0.0197	0.0230

Stock with a positive expected return should generate a greater return on the investment funded by the investors. The results of the estimated CAPM expected return for each market condition are shown in Table 8.

The highest and lowest expected return was obtained from TPIA (5.44%) and CPIN (-3.94%) shares in bullish conditions.

In bearish conditions, the highest and lowest expected return was obtained from SMMA (8.52%) and BBNI (-8.03%) shares. Under normal conditions, eight stocks produced a negative expected return, and nine stocks produced a return in bullish and bearish conditions. Stock with a negative expected return will not be involved in forming an optimal portfolio.

Black-Litterman model

a. Investor's View
The viewpoint concerns investors forecasting future stock returns, formed us using the absolute view. Table 9 shows the view vector of investors containing the predicted returns for each stock.

b. Optimum portfolio risk and return
Combining the CAPM expected return vector with the investor's view produces a Black-Litterman (μ_{BL}) expected return vector. The expected return of the Black-Litterman combination for stock in each market condition is presented in Table 10.

EMTK shares provided the highest expected return in each market condition, 15.16% and 14.80% in bullish and bearish conditions. Meanwhile, KLBF shares yielded the lowest expected return in each market condition at -0.56% and 0.023% in bullish and bearish conditions. TLKM exhibited the highest proportion, 72.04%, during bullish conditions. In contrast, MYOR held the largest proportion, 69.20%, during bearish conditions.

Several listed stocks had negative proportions, with short sales in the Black-Litterman weighting. The stocks with a negative proportion were not involved in forming portfolios.

After conducting the selection process based on β stock W_{BL}, a portfolio of four stocks in bullish condition was obtained. The portfolio included TLKM, TPIA, EMTK, and MYOR and five stocks in bearish condition: BBCA, TLKM, UNTR, EMTK, and MYOR.

The information in Table 11 is then used to calculate the return and risk of the portfolio. The estimated return and portfolio risk in each market condition are shown in Table 12.

In bullish conditions, the formed portfolio can provide a return of 8.90% with a risk of 4.34%. In bearish conditions, the formed portfolio yielded a return of 8.58% with a risk of 5.27%. Forming a Black-Litterman-based portfolio produced returns not different for each market condition. However, it provided a relatively large difference in risk, where bullish conditions are riskier than bearish. Therefore, it has been proven that both bullish and bearish portfolios tend to generate higher returns and lower risks compared to individual stock returns and risks. This observation leads to the conclusion that the portfolio is effectively diversified.

Table 9
Investor Views

Share	Return Prediction	Absolute View
BBCA	0.0782	Predict BBCA stock will give a return of 7.82%.
TLKM	0.1169	Predict TLKM stock will give a return of 11.69%.
UNVR	-0.0313	Predict UNVR stock will give a return of -3.13%.
HMSP	0.0308	Predict HMSP stock will give a return of 3.08%.
TPIA	0.0630	Predict TPIA stock will give a return of 6.30%.
ICBP	-0.0039	Predict ICBP stock will give a return of -0.39%.
CPIN	0.0012	Predict CPIN stock will give a return of 0.12%.
UNTR	0.1152	Predict UNTR stock will give a return of 11.52%.
EMTK	0.2798	Predict EMTK stock will give a return of 27.98%.
GGRM	0.0003	Predict GGRM stock will give a return of 0.03%.
KLBF	-0.0150	Predict KLBF stock will give a return of -1.50%.
MYOR	0.0734	Predict MYOR stock will give a return of 7.34%.

Table 10
Expected Return and Share Proportion

Share	Bullish Condition		Bearish Condition	
	(μ_{BL})	$(\boldsymbol{W}_{BL})$	$(\boldsymbol{\mu}_{BL})$	$(\boldsymbol{W}_{BL})$
BBCA	0.0405	0.2334	0.0408	0.1441
TLKM	0.0738	0.7204	0.0666	0.4722
UNVR	-	-	-	-
HMSP	0.0174	-0.0562	-	-
TPIA	0.0587	0.1404	-	-
ICBP	0.0047	-0.1174	0.0145	-0.0164
CPIN	-	-	0.0278	-0.0491
UNTR	-	-	0.0763	0.2091
EMTK	0.1516	0.3537	0.1480	0.1033
GGRM	0.0114	-0.0226	0.0063	-0.0341
KLBF	-0.0056	-0.4598	0.0023	-0.5211
MYOR	0.0466	0.2080	0.1517	0.6920

Table 11
Black-Litterman Portfolio Composition

Share	Bullish Condition		Bearish Condition	
	(μ_{BL})	$(\boldsymbol{W}_{BL})$	$(\boldsymbol{\mu}_{BL})$	$(\boldsymbol{W}_{BL})$
BBCA	-	-	0.0408	0.1375
TLKM	0.0738	0.4261	0.0666	0.4365
TPIA	0.0587	0.1351	-	-
CPIN	-	-	-	-
UNTR	-	-	0.0763	0.1688
EMTK	0.1516	0.2776	0.1480	0.2151
MYOR	0.0466	0.1613	0.1517	0.0422

Table 12
Portfolio Return and Risk

Bullish Condition		Bearish Condition	
Return	Risk	Return	Risk
0.0890	0.0434	0.0858	0.0527

A robustness test was conducted to provide additional support for the findings. The test used the same model and considered the same period as before. However, the benchmark did not account for the switching between bullish and bearish market conditions. The portfolio's performance was evaluated using the information ratio assessment. By assuming that stock returns are normally distributed, the results are shown in Table 13.

Table 13
Information Ratio

Market Condition	Information Ratio
Bullish	1.4381
Bearish	0.1788

Information ratio values greater than zero indicate that at least 50% of the portfolio in bullish and bearish conditions provides higher returns than the benchmark. Therefore, portfolios formed under bullish and bearish conditions perform better than under bullish and bearish conditions.

Conclusion and Implications

In conclusion, between January 2011 and December 2020, the Indonesian capital market was bullish and bearish for 77 and 43 months, with an expected duration of 6.38 and 1.78 months, respectively.

In bullish and bearish conditions, JCI generated a profit and loss of 2.03% and 5.49% per month, with a volatility of 0.02% and 0.06%, respectively. The probability of the conditions remaining bullish and bearish was 84.33% and 43.83%. Meanwhile, the transition probability from bullish to bearish and bearish to bullish condition was 15.67% and 56.14%, respectively.

The optimal portfolio composition in bullish condition consisted of four stocks, namely TLKM (42.61%), EMTK (27.76%), MYOR (16.13%), and TPIA (13.51 %), with a return of 8.90% and a risk of 4.34%.

Furthermore, the optimal portfolio composition in bearish condition consists of five stocks, namely TLKM (43.65%), EMTK (21.51%), UNTR (16.88%), BBCA (13.75%), MYOR (4.22%) with a return of 8.58% and a risk of 5.27%. The robustness test showed that the optimal portfolio constructed in bullish and bearish periods performed better than those constructed without taking the market condition.

Implication, Limitations, and Suggestions

The study has shown that the Black-Litterman model has the potential to enhance portfolio performance and provide investors with a more efficient and effective method of asset allocation. By combining the Black-Litterman and Markov-switching models, investors can reduce the effect of estimation errors and uncertainties in asset pricing.

This study provides investors with a comprehensive overview of capital market conditions between January 2011 and December 2020. It offers valuable insights and guidance for investors to compile stock portfolios in bullish and bearish conditions effectively. By understanding the market trends and being aware of possible risks associated with changing market conditions, investors can better prepare themselves and make informed investment decisions.

This study uses the original Black-Litterman model, where the empirical estimation of the equilibrium employs the CAPM. In addition, this study assumes that stock returns are normally distributed with a linear relationship and do not apply to all market conditions.

For further study, the Black-Litterman model can be developed using the nonparametric or flexible model to predict returns and investor views. This flexibility may be more beneficial because it does not require assumptions of normality or linear relationship between stock, and a flexible model enables the practical calculation of the equilibrium point, reducing the requirement for parametrization. This study can be continued by examining the performance differences between the Black-Litterman, Markowitz, and CAPM portfolios in bullish and bearish conditions.

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