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Advanced Value at Risk Modeling with Fifth-Moment Cornish–Fisher Expansion for IDX SMC Composite Consumer Cyclicals

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A B S T R A C T :

The analysis of the IDX SMC Composite in the Consumer Cyclicals sector was conducted during several major events, including the COVID-19 pandemic and various political developments, which contributed to non-normal data characteristics. The portfolio was constructed using the Mean–Semivariance method, which does not require the assumption of normally distributed returns. Portfolio risk was measured using Value at Risk (VaR) with the Cornish–Fisher Expansion, a method suitable for non-normal data and extendable to the fourth and fifth moments. This study estimated VaR using the fifth-moment Cornish–Fisher Expansion for a portfolio derived from the Mean–Semivariance approach. The dataset consisted of daily closing prices of stocks in the IDX SMC Composite Consumer Cyclicals sector from January 2020 to February 2024. The optimal portfolio comprises four stocks: PT Jakarta Setiabudi Internasional Tbk (JSPT) with a weight of 48.12%, PT Mitra Adiperkasa Tbk (MAPB) with 26.01%, PT Multipolar Technology Tbk (MLPT) with 21.67%, and PT Tifico Fiber Indonesia Tbk (TFCO) with 4.01%. The portfolio risks obtained from the fourth- and fifth-moment Cornish–Fisher Expansion VaR are –1.72% and –2.66% at the 95% confidence level, respectively, with the fifth moment indicating a higher level of risk.

Keywords: Portfolio; Mean-Semivariance; Value at Risk; Cornish Fisher Expansion

1. Introduction

The capital market plays an important role in driving Indonesia's economic growth by providing companies with access to capital. It serves as an alternative source of financing, enabling firms to expand their operations and increase revenue. Investors use stock market indices, such as the IDX SMC Composite, as a reference for making investment decisions. The Consumer Cyclicals sector, which is part of the IDX SMC, is influenced by fluctuations in Indonesia's economic conditions (Fitriyani *et al.*, 2022). Political instability can create uncertainty that affects stock prices (Hidayat, 2018). The COVID-19 pandemic and political events have also influenced stock price movements.

Portfolio theory emphasizes the importance of diversification in minimizing investment risk. Diversification is a strategy used to mitigate greater risk by allocating capital across multiple companies. Markowitz (1952) introduced a portfolio optimization method to achieve a given level of return and risk. One of the approaches used in portfolio formation is the Mean–Semivariance method, which is more sensitive to asymmetry in asset return distributions (Borovička, 2022). The Mean–Semivariance approach can be applied under both normal and non-normal data distributions.

Portfolio theory states that portfolio construction must take risk and return into account (Firdaus *et al.*, 2022). Value at Risk (VaR) is an estimate of the maximum potential loss that may occur within a specific period at a given confidence level (Liman *et al.*, 2023). Traditional VaR measurement assumes that return data follow a normal distribution. The Cornish–Fisher Expansion–based VaR (VaR-ECF) method is used to measure risk in non-normal conditions (Maruddani & Astuti, 2021). Abdurakhman (2019) showed that the fifth-moment method empirically provides higher accuracy compared to standard models, as indicated by smaller errors. The maximum loss estimation under the Cornish–Fisher Expansion VaR approach can be extended using the fifth moment.

This study aims to apply the Mean–Semivariance method and the fifth-moment VaR-ECF using data from the Consumer Cyclicals sector of the IDX SMC Composite. The objective is to estimate the worst possible loss in forming an optimal portfolio over a period that includes events such as the COVID-19 pandemic and political developments.

2. Theoretical Framework

Return consists of realized return and expected return (Silalahi and Sianturi, 2021). Realized return is the rate of return obtained from historical data, calculated as the difference between the current investment price and the price in the previous period. Expected return refers to the rate of return anticipated by investors in the future. Stock returns are calculated using continuously compounding returns or logarithmic returns. According to Jorion (2007), stock returns can be expressed by equation (1):

$$= \ln\left(\frac{\;'\;}{P_{i,t-1}}\right) \quad (1)$$

The expected return of a stock is the level of profit anticipated from an investment in a particular issuer (Firdaus *et al.*, 2022). According to Jorion (2007),

$$E(R_t) = \frac{1}{n}\sum_{=1} R_{i,t} \quad (2)$$

Description: $R_{i,t}$ is return of stock $i$at time t; $P_{i,t}$ is price of stock i at time t; $P_{i,t-1}$ is price of stock i at time $t-1$; i is index of the stock; $E(R_t)$ is number of observations.

Investment decisions involve risk analysis to evaluate potential losses. Stock risk refers to the difference between the expected return and the actual return, measured using the variance or standard deviation of investment returns. This risk arises due to fluctuations and instability in stock prices. The risk of stock investment can be calculated using equation (3), which represents the second moment.

$$\sigma_i^2 = \frac{1}{n-1}\sum_{=1}(R_{,} - \mu)^2 \quad (3)$$

Correlation coefficients are statistical measures that assess the relative movement between two variables. This metric describes the extent to which the returns of different securities are related to one another. Correlation values range from perfectly negative (–1.0) to perfectly positive (+1.0). A commonly used nonparametric correlation measure for non-normal data and at least ordinal-scale variables is Kendall's Tau. The Kendall Tau correlation formula for a sample of size n with $n_0 = 0.5n(n-1)$ is defined as follows (Puth *et al.*, 2015):

$$= \frac{n_c - n_d}{0} \quad (4)$$

r is Kendall Tau correlation coefficient; n_c is number of concordant pairs; n_c is number of discordant pairs. A portfolio is a combination of investments in various financial instruments, commonly known as diversification (Samsul, 2006). Portfolio management, often referred to as diversification, involves composing a mix of investment instruments with the aim of complementing one another by combining several stocks or single securities to reduce the risk of asset ownership. An efficient portfolio is one that yields a high expected return for a given level of risk or minimizes risk for the same level of expected return (Firdaus et al., 2022). An optimal portfolio is a portfolio that aligns with the investor's preferences, with asset weights denoted by $\boldsymbol{w_i}$. The portfolio return is presented in equation (5)

$$R_{port} = [w_1 \quad w_2 \quad \cdots \quad w_m]\begin{bmatrix} 1 \\ R_2 \\ \cdots \end{bmatrix} = \boldsymbol{w^T R} \quad (5)$$

with the expected return of the portfolio calculated as follows:

$$E(R_p) = \mu_p = \sum_{=1} w_i \mu_i \quad (6)$$

the portfolio variance is given as follows:

$$(\quad) = \quad (7)$$

Where $\boldsymbol{w}$ is portfolio weight matrix; $\boldsymbol{\Sigma}$ is variance–covariance matrix; w_i is weight of asset i; R_p is portfolio return; is variance of asset $\boldsymbol{i}$; σ_{ij} is covariance between asset $\boldsymbol{i}$ and asset $\boldsymbol{j}$.

The Mean–Semivariance approach is a portfolio construction method that serves as an alternative to methods requiring the assumption of normal distribution, as it can be applied to both normally and non-normally distributed data. The semivariance equation proposed by Markowitz exhibits endogeneity because portfolio weights are influenced by periods in which the portfolio falls below the benchmark. The benchmark selected by an investor may take the form of zero return, the risk-free interest rate, a particular stock market index, or the average return of a given portfolio (Salah et al., 2018). According to Estrada (2008), the semivariance equation for the return of asset **i**relative to the benchmark is:

$$S^2 = \frac{1}{\_}\sum_{=1}[Min(R - B, 0)]^2 \quad (8)$$

The semicovariance equation between assets and is as follows:

$$S_{ijB} = \frac{1}{n}\sum_{=1}[Min(R_{it} - B, 0).Min(R_{jt} - B, 0)] \tag{9}$$

with ^{2} is semivariance of asset with respect to benchmark ; is semicovariance between assets and with respect to benchmark ; is return of asset at time ; is return of asset at time .

The semivariance of the stock portfolio is given in equation (10) as follows:

$$S\ ^2 = \frac{1}{\_}\sum_{=1} w\, w\, S \tag{10}$$

with $S_{pB}{}^2$ is portfolio semivariance; w_i is weight of asset i; w_j is weight of asset j.

The semivariance–semicovariance matrix, denoted as **Σ**sv, is defined as follows

$$\mathbf{\Sigma}\text{sv} = \begin{bmatrix} S_{iB}{}^2 & \cdots & S_{imB} \\ \vdots & \ddots & \vdots \\ S_{miB} & \cdots & S_{mB}{}^2 \end{bmatrix}$$

The optimal value of w obtained will minimize the portfolio risk under the constraint that the sum of the portfolio weights equals one. The Lagrange function is written in Equation (11).

$$L = \boldsymbol{w^T}\, \boldsymbol{\Sigma_{sv} w} + \lambda_1(\boldsymbol{\mu_p} - \boldsymbol{w^T \mu_p}) + \lambda_2(\boldsymbol{1} - \boldsymbol{w^T 1_m}) \tag{11}$$

where L is the Lagrange function; $\boldsymbol{w}$ is the asset weight vector; $\boldsymbol{\Sigma_{sv}}$ is the semivariance–semicovariance; λ_1 and $\lambda_2$are the Lagrange multiplier; $\boldsymbol{\mu_p}$ is the mean portfolio return; and $\boldsymbol{1_m}$ is a vector of ones with dimension $m \times 1$.

For an efficient semivariance portfolio, there is no constraint on the portfolio mean ($\lambda_1 = 0$). The weighting in the mean–semivariance framework is expressed in Equation (12).

$$= \frac{\boldsymbol{\Sigma_{sv}}^{-1}\boldsymbol{1_m}}{^{-1}\boldsymbol{1_m}} \tag{12}$$

Portfolio construction involves measurable risks. One of the tools commonly used to quantify such risks is Value at Risk (VaR), which typically assumes that stock returns follow a normal distribution under normal market conditions. The VaR approach based on the Cornish–Fisher Expansion can be applied to data that do not follow a normal distribution. Various statistical moments—such as skewness, kurtosis, and hyper-skewness—are incorporated, with skewness representing the third-order central moment, kurtosis representing the fourth-order central moment, and hyper-skewness representing the fifth-order central moment (Selvan et al., 2022). The definition of the k-th order moment is given in Equation (13) as follows:

$$= \frac{\mathrm{E}[(X - E[X])^k]}{\sigma^k} \tag{13}$$

Skewness is a measure of the asymmetry of a distribution curve (Atqan and Kudus, 2023). It is used to assess the degree of non-symmetry in a distribution. The skewness measure based on the third central moment can be computed using Equation (14).

$$= \frac{\mathrm{E}[(X - E[X])^3]}{\sigma^3} \tag{14}$$

Kurtosis is a statistical parameter that measures the degree of peakedness or sharpness of a distribution. The kurtosis of a distribution curve is calculated using Equation (15).

$$= \frac{\mathrm{E}[(X - E[X])^4]}{\sigma^4} \tag{15}$$

Hyper-skewness for the distribution curve is calculated using Equation (16). Incorporating moments up to the fifth order allows for a more in-depth analysis of the distribution of investment returns. This enables a more comprehensive understanding of risk, including risks that may not be captured by simpler analytical approaches.

$$= \frac{\mathrm{E}[(X - E[X])^5]}{\sigma^5} \tag{16}$$

where is skewness measure; is kurtosis measure; is hyper-skewness measure; [ ] is expected return; and is standard deviation.

According to Maruddani (2019), a distribution exhibiting excess kurtosis has a narrower but much higher peak and heavier tails compared to a normal distribution. The excess kurtosis for the variable , representing stock returns, is expressed in Equation (17).

$$\psi(X) = K(X) - 3 \tag{17}$$

According to Maruddani (2019), the Cornish–Fisher Expansion formula incorporating the fifth-order moment with the α-quantile is expressed in Equation (18).

$$= \quad + \frac{((q_\alpha)^2 - 1)S(X)}{6} + \frac{((q_\alpha)^3 - 3q_\alpha)\psi(X)}{24} - \frac{(2(q_\alpha)^3 - 5q_\alpha)S^2(X)}{36} \tag{18}$$

According to Holton (2013), the Cornish–Fisher Expansion method incorporating the fifth-order moment in the form of the α-quantile is given in Equation (19).

$$= \quad + \frac{((q_\alpha)^2 - 1)S(X)}{6} + \frac{((q_\alpha)^3 - 3q_\alpha)\psi(X)}{24} - \frac{(2(q_\alpha)^3 - 5q_\alpha)S^2(X)}{36} + \frac{((q_\alpha)^4 - 6q_\alpha)HS(X)}{120} - \frac{((q_\alpha)^4 - 5(q_\alpha)^2)S(X)\psi(X)}{24} + \frac{(12(q_\alpha)^4 - 53(q_\alpha)^2 + 17)S^3(X)}{324} \tag{19}$$

The measurement of maximum loss uses the initial investment value V_0 and the investment horizon T. According to Maruddani (2019), the estimated Value at Risk using the Cornish–Fisher Expansion is formulated in Equation (20).

$$VaR^{ECF}(R \quad) = -V_0 \times (\mu \quad - ECF\,\sigma \quad) \times \sqrt{T} \tag{20}$$

3. Methods

This study uses secondary data obtained from the Yahoo Finance website and the Indonesia Stock Exchange. The data consist of daily closing prices of stocks listed in the IDX SMC Composite Consumer Cyclicals sector and the IHSG, covering the period from January 2020 to February 2025. The main variable is stock return, derived from stocks included in the IDX Small-Mid Capital Composite within the Consumer Cyclicals sector, along with IHSG data from 1 February 2024 to 31 July 2025. The observed stocks include Ace Hardware Indonesia Tbk. (ACES), PT Argo Pantes Tbk (ARGO), PT Arthavest Tbk (ARTA), PT Astra Otoparts Tbk (AUTO), and others, totaling 47 stocks. The data analysis steps are as follows:

1. Calculate the returns of each stock and the IHSG for the specified period.
2. Select stocks with positive expected returns, significantly positive skewness, and negative correlations with one another.
3. Compute the semivariance and semicovariance for the selected stocks.
4. Determine the weight of each security using the Mean–Semivariance method to form the optimal portfolio.
5. Calculate the return of the constructed stock portfolio.
6. Determine the expected return of the portfolio.
7. Compute the first through fifth moments as preliminary steps for risk measurement.
8. Calculate the Value at Risk (VaR) using the fifth-moment Cornish–Fisher Expansion approach.

4. Results and Discussions

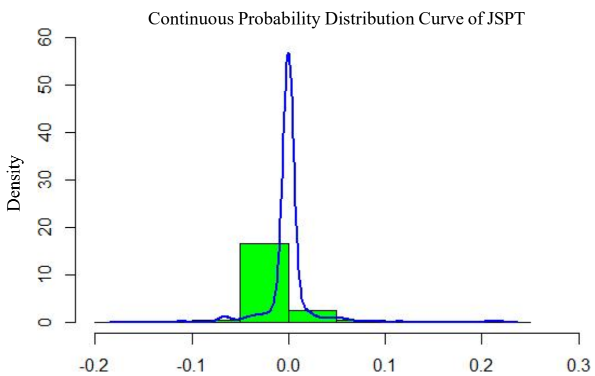

Fig. 1 - Histogram of JSPT Stock Return Distribution for the Period 1 January 2020 – 29 July 2025.

Figure 1 presents one of the return distribution histograms from the total of 47 stocks observed during the period 1 January 2020 – 29 July 2025. The return distribution histogram of JSPT shows positive skewness, indicated by a longer tail on the right side of the distribution. The presence of positive or negative skewness across the 47 stocks suggests a higher level of instability risk, as the data deviate from normality. This condition may pose challenges in managing portfolio risk effectively.

The expected return is the average return of each stock. The expected returns during the study period show that the 47 stocks experienced both gains and losses, as presented in Table 1. Table 1 shows that 23 of these stocks have positive expected returns, indicating that investments in these stocks generated profits. The positive returns obtained by a substantial portion of the stocks suggest potential for portfolio growth during the period.

Table 1. Summary of Stock Expected Returns

Code	Expected Return	Code	Expected Return	Code	Expected Return
ACES	-0.000585	IIKP	0.0000000	MSIN	0.002601
ARGO	0.000053	IMAS	0.000338	NATO	-0.001736
ARTA	0.001769	INDR	0.000399	PBRX	-0.001926
AUTO	0.000584	INDS	0.000048	PJAA	-0.000041
BOGA	-0.000174	IPTV	-0.002283	PMJS	0.0000000
BOLT	-0.000086	JGLE	0.0000000	PZZA	-0.001285
BRAM	-0.000597	JSPT	0.000261	RALS	-0.000751
BUVA	-0.00035	KPIG	-0.000784	SCMA	-0.000612
CARS	-0.000591	LPPF	-0.000817	SHID	-0.000856
CSAP	0.00028	MAPA	0.000769	SRIL	-0.000562
ERAA	0.000255	MAPB	0.000169	TFCO	0.000502
FAST	-0.000553	MAPI	0.000582	TRIO	0.0000000
GJTL	0.000697	MASA	0.002145	WOOD	-0.000632
GWSA	-0.000053	MLPT	0.001222	BLTZ	-0.000451
HOME	0.0000000	MNCN	-0.001586	MDIA	-0.000076
HRTA	0.000595	MPMX	0.000446		

Skewness is a statistical measure that describes the degree of asymmetry in a data distribution. A positive skewness value indicates that the distribution has a longer tail on the right side. Kurtosis provides information on how peaked or flat a distribution of returns or asset prices is, indicating how frequently extreme values occur within the distribution.

Table 2. Skewness and Kurtosis Values

Code	Skewness	Kurtosis	Code	Skewness	Kurtosis
ARGO	-26.63448	797.18145	JGLE	-	-
ARTA	1.77976	9.99570	JSPT	2.70472	32.64278
AUTO	0.25247	3.82892	MAPA	0.92366	4.91711
CSAP	0.58870	5.53431	MAPB	1.54138	8.64417
ERAA	0.66248	5.37763	MAPI	0.65541	3.20529
GJTL	1.99602	13.45654	MASA	1.70300	6.91568
HOME	-	-	MLPT	2.36286	10.99296
HRTA	1.71432	12.34470	MPMX	0.90831	7.21059
IIKP	-	-	MSIN	2.10282	17.48071
IMAS	1.64931	7.82370	TFCO	1.66943	11.09822
INDR	1.23584	12.07480	TRIO	-	-
INDS	1.16873	11.08480			

The skewness and kurtosis values of the stocks were calculated using equations (14) and (15), as presented in Table 2. Based on Table 2, a total of 12 out of 23 IDX Small-Mid Capital Composite stocks with positive expected returns exhibit high skewness values. Positive skewness indicates the potential for large gains.

The assessment of correlation coefficients between stocks was conducted using the Kendall Tau correlation method, which is used to determine the relationship between two variables with data that are at least ordinal in scale. The concept of diversification involves reducing risk by combining assets with low or negative correlations within a portfolio. Table 4 presents the stocks with stronger negative correlations.

Table 3. Correlation Among Stocks

	JSPT	MAPB	MLPT	TFCO
JSPT	1,00000000	-0,04085031	-0,01378210	-0,03107898

MAPB	-0,04085031	1,00000000	-0,03412084	-0,01287755
MLPT	-0,01378210	-0,03412084	1,00000000	-0,02377549
TFCO	-0,03107898	-0,01287755	-0,02377549	1,00000000

Table 4 shows that the negative correlation values are very low, ranging from –0.01 to –0.199, indicating that the returns of the securities move in different directions. From a total of 48 stocks, four IDX Small-Mid Capital Composite stocks in the Consumer Cyclicals sector were selected for inclusion in the portfolio: PT Jakarta Setiabudi Internasional Tbk (JSPT), PT Mitra Adi Perkasa Tbk (MAPB), PT Multipolar Technology Tbk (MLPT), and PT Tifico Fiber Indonesia Tbk (TFCO).

Portfolio weighting is used to determine the allocation of funds to each stock in order to achieve an optimal portfolio. The calculation of weights begins with determining the semivariance of each asset's return and the semicovariance between stock returns. After obtaining the semicovariance matrix, matrix inversion is performed to derive the portfolio weights. The resulting portfolio weights for each stock are presented in Table 4. Table 4 shows the portfolio weights: JSPT (w_1) at 0.48121781 or 48.12%, MAPB (w_2) at 0.26009572 or 26.01%, MLPT (w_3) at 0.21674014 or 21.67%, and TFCO (w_4) at 0.04194629 or 4.20%.

Table 4. Portfolio Weights

Code	Semicovariance Value
JSPT	0.48121781
MAPB	0.26009572
MLPT	0.21674014
TFCO	0.04194629

Moments are statistical parameters used to measure the characteristics of a distribution. The mean and variance are important parameters, with the mean referred to as the first moment and the variance as the second moment. In addition to these, there are other significant moments: the third moment, known as skewness; the fourth moment, known as kurtosis; and the fifth moment, referred to as hyper-skewness. Information on the results of these moment calculations is presented in Table 5.

Table 5. Results of Portfolio Return Moment Calculations

Moment	Value
First Moment	0.000455
Second Moment	0.000243
Third Moment	1.435778
Fourth Moment	8.861987
Fifth Moment	49.106400

The Cornish–Fisher Expansion method is an approach used to calculate Value at Risk (VaR) for data that do not follow a normal distribution. The VaR calculation using the Cornish–Fisher Expansion begins by computing the ECF (Cornish–Fisher Expansion) value. The excess kurtosis value is 5.861987. The ECF value for the fourth moment, calculated using the formula in equation (18), is as follows:

$$ECF = -1.64 + \frac{((1.64)^2 - 1)(1.435778)}{6} + \frac{((1.64)^3 - 31.64)(5.861987)}{24} - \frac{(2(1.64)^3 - 5(1.64))(1.435778)^2}{36} = -1.079704$$

The ECF value for the fifth moment, calculated using the formula in equation (19), is as follows:

$$= (1.64) + \frac{((1.64)^2 - 1)(1.435778)}{6} + \frac{((1.64)^3 - 3q_\alpha)(5.861987)}{24} - \frac{(2(1.64)^3 - 5(1.64))(1.435778)^2}{36} + \frac{((1.64)^4 - 6(1.64))(49.106400)}{120} - \frac{((1.64)^4 - 5(q_\alpha)^2)(1.435778)(5.861987)}{24}$$

$$+ \frac{(12(q_\alpha)^4 - 53(q_\alpha)^2 + 17)(1.435778)^3}{324} = -1.674758$$

The Cornish–Fisher Expansion (ECF) value up to the fourth moment using equation (18) is –1.079704, while the ECF value up to the fifth moment using equation (19) is –1.674758. The results show a slight difference between the ECF values for the fourth and fifth moments. The difference between the two values is 0.009279, with the fifth-moment ECF yielding a higher risk value. The Cornish–Fisher Expansion approach is applied in the VaR calculation using the formula in equation (20), and the output generated from RStudio is presented in Table 6.

Table 6. VaR Calculation Results

	VaR 95% (1 day)
VaR up to the Fourth Moment	0.01729193
VaR up to the Fourth Moment	0.02657109

Based on Table 6, the estimated VaR at the 95% confidence level using the ECF up to the fourth moment is 0.01729193 for a one-day holding period. This indicates that if an investor allocates Rp100,000,000.00 to the portfolio, the maximum potential loss would not exceed Rp1,729,193.00 within one day after 29 February 2024. Meanwhile, the VaR estimate using the ECF up to the fifth moment is 0.026571 for the same one-day holding period, meaning that the maximum potential loss would not exceed Rp2,657,109.00 over the same period.

4. Conclussions

The construction of a stock portfolio for the IDX SMC (Small Mid Capital) Composite Index in the Consumer Cyclicals sector for the period January 2020–February 2024 using the Mean–Semivariance method resulted in an optimal portfolio with weights of 48.12% for PT Jakarta Setiabudi Internasional Tbk (JSPT); 26.01% for PT Mitra Adi Perkasa Tbk (MAPB); 21.67% for PT Multipolar Technology Tbk (MLPT); and 4.01% for PT Tifico Fiber Indonesia Tbk (TFCO). The VaR calculation using the Cornish–Fisher Expansion up to the fourth and fifth moments for the optimal portfolio of IDX SMC Composite stocks in the Consumer Cyclicals sector during the period 1 January 2020 – 29 February 2023, at a 95% confidence level and a one-day holding period, yields risk values of –1.73% and –2.66%, respectively. In conclusion, the risk estimates using the Cornish–Fisher Expansion Value at Risk up to the fifth moment produce higher values compared to the method applied only up to the fourth moment.

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