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IMPLEMENTATION OF STOCHASTIC MODEL FOR RISK ASSESSMENT ON INDONESIAN STOCK EXCHANGE

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Abstract: Currently, financial assets become an alternative choice for investors in Indonesia to get maximum profits. The Indonesia Stock Exchange is the official capital market in Indonesia which is a place for trading financial assets. Stocks are listed as the most preferred financial asset by investors. In reality, stock investment is not a risk-free investment. The main risk that investors should face is the loss risk. This kind of risk can occur at any time. From that problem, this study aims to do risk assessment on the Indonesian stock market. The evaluation will be started with stock price index prediction using the Stochastic model (Geometric Brownian Motion Model and Jump Diffusion). Then, the result from that processes will be used to get loss risk prediction through the Adjusted Expected Shortfall model. By using the historical price of JKSE index from 01/08/21 to 31/08/22, Jump Diffusion is the best model to predict the JKSE index with MAPE value is 1.08%. Then, at the 95% confidence level and 1-day holding period, the expected loss risk using Adjusted Expected Shortfall model on 09/01/2022 is -0.02978.

1. INTRODUCTION

Financial assets are one type of asset that can be an option in investing (Gao et al., 2022). The value of financial assets obtained from contractual rights or ownership claims (Liu et al., 2019). In Indonesia, investment in financial assets has increased significantly in the last 5 years (IDX Indonesia, 2022). This increase refers to the number of investors listed on the Indonesia Stock Exchange as the authorized capital market in Indonesia. According to the report of the Indonesian Central Securities Depository (KSEI), in 2017 the number of investors registered on the Indonesia Stock Exchange was 1,025,414, and in April 2022 it increased to 8,620,911. The percentage increase in the number of investors within 5 years is 740.73%. (KSEI, 2022)

Based on the KSEI report, in 2022 the investors who are officially registered on the Indonesia Stock Exchange are most investors in stock assets. KSEI noted that out of 8,620,911 investors, 4,023,442 were stock investors, in other words, stock investors contributed 46.67% to the total investors in IDX (KSEI, 2022). Compared to 2017, the number of stock investors in IDX Indonesia is still at 851,662. According to Wibowo et al. (2019), The increase in the number of investors who allocate their funds to stock assets is driven by several reasons, including: (i) the value of stock assets can be stable in inflationary conditions; (ii) the stock is an asset that is easy to buy and the transaction is simple; (iii) to start investing in stocks, an investor does not need a lot of capital.

The benefits of stocks investment can provide a high salary in a short time. In each time period, the value of return on income is influenced by stock price movements (Purnamasari, 2015). Li et al. (2022) state that stocks price has dynamic price movements and can change in a short time. This is a challenge for investors and financial managers to be able to predict stock prices in the future with accuracy. The ability to predict stocks is crucial because the prediction results obtained can be used to measure the expected return and the value of loss risk (Ji et al. (2020). In every stock market, there is an index called the stock market index. This index is used to measure the stock price performance of all companies listed on the related stock market (IDX Indonesia, 2022). Furthermore, a stock market index helps the investors to tracks the movement of all stocks listed on that stock market.

Fathali et al. (2022) explained, investor can utilize the stock market index to predict the performance of all companies in the future, and the estimated return value. So, we need an appropriate quantitative model according to the characteristics of the stock market index in the observation period. Theoretically, the movement of the stock market index is a stochastic process whose movements are influenced by past volatility (Islam and Nguyen, 2020). Therefore, Stochastic Model is a tool to predict the stock market index. In this study, the stochastic models that we will use are Geometric Brownian Motion (GBM) and Jump Diffusion model. GBM can be used when historical returns of market index are normally distributed (Guloksuz, 2021). When historical return of market index is normally distributed with heavy tail or not normally distributed, we can used Jump Diffusion model (Ma and Li, 2019). After we obtain the stock market index prediction, the predicted value will be used to measure the loss risk value. The loss risk is important to estimate accurately because it is related to the risk management strategy that must be prepared by investors (Rahmawati et al, 2019). We proposed Adjusted Expected Shortfall (Adj-ES) as risk measure to forecast loss risk. Adj-ES firstly used by Jadhav et al. (2013) to measure losses on the Indian stock market. This model is an improvement from Value at Risk and Expected Shortfall, which are considered capable of being more efficient in predicting risk without losing coherence (Trimono et al., 2019).

Several previous studies that examined the application of the Stochastic Model to predict the value of the stock market index or loss risk value, among others, are Chiu, et al. (2017) applicated stochastic volatility for forecast loss risk with VaR model. They got conclusion if the VAR model with disturbances results in density forecasts for industrial production and stock returns that are superior to alternatives that assume Gaussianity. The second, Chan (2017) used Stochastic Model with time-varying parameters to modeling the inflation in United States, Germany, and United Kingdom at 2016. The estimation results show substantial time-variation in the coefficient associated with the volatility, highlighting the empirical relevance of the proposed extension. Zhang et al. (2020) introduce stochastic models with ARMA innovations to forecast inflation on G7 country members. Then, form this research they find that the new models generally provide competitive point and density forecasts compared to standard benchmarks, and are especially useful for Canada, France, Italy, and the U.S. And the last, Tiwari (2019) analyze and modelling the dynamic of the Bitcoin and Litecoin with stochastic volatility models and compared it with GARCH. By using historical price along 2018 and 2019, the comparison of GARCH models with GARCH-GJR models reveals that the leverage effect is not significant for cryptocurrencies, suggesting that these do not behave like stock prices.

This study aims to analyze the value of risk of loss and estimates of JKSE as stock market index on IDX Indonesia through Stochastic Volatility Model and Adj-ES risk measure. The combination of the two models is a novelty offered in this study. The data used is the historical price of JKSE from 01/08/21 to 31/08/22. The analysis will begin with building a predictive model and continue with the prediction of the risk of loss.

2. LITERATURE REVIEW

2.1. Stochastic Model for Stock Market Index Prediction

In general, the stochastic model is kind of financial model which help investors make investment decisions. This model used random variable to forecast possible future outcomes under uncertainty condition. In addition, Antwi (2017) state that Stochastic models used for most practical situations in financial and economics sector, that need to account for a high number of scenarios. The reduction of the number of scenarios considered to solve the problem can improve the efficiency in the resolution of these problems. In other side, by using stochastic model, it is possible to get several different prediction results about the condition in the future.

2.1.1. Geometric Brownian Motion (GBM) Model

GBM is widely used in financial asset modelling. This model is useful for predicting asset prices based on historical returns (Hersugondo et al., 2022). The GBM model will effectively apply if the company and the market are in stable condition, the stock price of the company considered continuous in time, and the stock return value assumed normally distributed (Maruddani and Trimono, 2017). To obtain the equations of the GBM model, look at the PDS with the drift term $\mu S(t)$ and the diffusion term $\sigma S(t)$ as follows (Trimono et al., 2017)

$$dS(t) = \mu S(t)dt + \sigma S(t)dW(t) \tag{1}$$

Since $W(t)$ is a standard Brownian motion, the completeness property of $W(t)$ implies that $W(t_i) - W(t_{i-1}) \sim \sqrt{t-s}$ Normal (0,1), then

$$S(t_i) = S(t_{i-1}) \exp\left(\left(\hat{\mu} - \frac{\hat{\sigma}^2}{2}\right) + \hat{\sigma} Z_{i-1}\right) \tag{2}$$

Expected value and confidence interval of prediction result on GBM Model

As a stochastic model, GBM has several properties, including the expected value. It will be a reference for the average of predicted value at a certain period. Suppose that $\hat{S}(t_i)$ be predicted value at period t_i. The expected value of $\hat{S}_t$ is defined as:

$$E\left(\hat{S}(t_i)\right) = E\left(S(t_{i-1}) \exp\left(\left(\hat{\mu} - \frac{\hat{\sigma}^2}{2}\right) + \hat{\sigma} Z_{i-1}\right)\right) \tag{3}$$

$$= E\left(S(t_{i-1})\exp\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right)\right)E(\exp(\hat{\sigma}Z_{i-1}))$$

Since Z_{i-1} ~ Normal (0,1), then E$(\exp(\hat{\sigma}Z_{i-1}))$ = $\exp\left(\frac{1}{2}\hat{\sigma}^2\right)$, so

$$\left(\hat{S}(t_i)\right) = S(t_{i-1})\exp\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right)\exp\left(\frac{1}{2}\hat{\sigma}^2\right) = S(t_{i-1})\exp(\mu) \tag{4}$$

For every $\hat{S}(t_i)$, note that $\ln\hat{S}(t_i)$ is normally distributed with mean $\ln\hat{S}(t_{i-1})$ + $\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right)$ and variance $\hat{\sigma}^2$. At (1-α) % significance level, the confidence interval of $\ln\hat{S}(t_i)$ are given by following equation:

$$\ln\hat{S}(t_{i-1}) + \left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right) - q_{1-\frac{\alpha}{2}}\hat{\sigma} \le \ln\hat{S}(t_i) \le \ln\hat{S}(t_{i-1}) + \left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right) + q_{1-\frac{\alpha}{2}}\hat{\sigma} \tag{5}$$

Then, by taking the exponential in (7), we obtain the (1-α) % confidence interval of the $\hat{S}(t_i)$ which follow lognormal distribution is:

$$\begin{aligned}&\exp\left(\ln\hat{S}(t_{i-1}) + \left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right) - q_{1-\frac{\alpha}{2}}\hat{\sigma}\right) \le \hat{S}(t_i)\\ &\le \exp\left(\ln\hat{S}(t_{i-1}) + \left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right) + q_{1-\frac{\alpha}{2}}\hat{\sigma}\right)\end{aligned} \tag{6}$$

2.1.2.Jump Diffusion Model

This model is the development of Geometric Brownian Motion, which is specifically used when historical returns are not normally distributed or the normality assumption is met but returns are heavy tailed. Li et al. (2019) states that the initial SDE model to obtain the Jump Diffusion model is expressed as:

$$d\,S(t) = (\mu - \lambda)S(t)dt + \sigma S(t)dW(t) + (y_t - 1)dQ(t) \tag{7}$$

where, μ and σ is the average and volatility of stock returns, $W(t)$ is standard Brownian Motion, and $Q(t)$ is Poisson process with intensity λ.

To solve Stochastic Differential Equation for obtain the Jump Diffusion stock price model can be obtained through the Ito theorem. If we have SDE as in equation (1), and we have the function $G = \ln S(t)$. Then, based on the Ito theorem, the following equation applies:

$$\begin{aligned}dG &= \left(\frac{1}{V}(\mu - \lambda)S(t) + 0 + \frac{1}{2}\left(-\frac{1}{S(t)^2}\right)\sigma^2 S(t)^2\right)dt + \frac{1}{S(t)}\sigma\,S(t)dW(t)\\ &\quad + G(S(\left(t + \Delta S(t)\right) - G\left(S(t)\right)\\ &= \left(\mu - \frac{1}{2}\sigma^2 - \lambda\right)dt + \sigma dW(t) + (\ln y_i)\end{aligned} \tag{8}$$

Furthermore, if the price change (Δt) is 1 day, then by integrating the two from t_{i-1} to t_i, we get:

$$S(t_i) = S(t_{i-1})\exp\left\{\left(\mu - \frac{1}{2}\sigma^2 - \lambda\right)(t_i - t_{i-1}) + \sigma W((t_i) - W(t_{i-1})\right\}\exp\prod_{j=1}^{Q_t} Y_j \tag{9}$$

where $ln\, y_i$ follows a normal distribution, then the Jump Diffusion model for stock price prediction is defined:

$$\hat{S}(t_i) = \hat{S}(t_{i-1})\exp\left(\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2 - \hat{\lambda}\right) + (\hat{\sigma}Z_{i-1}) + N_i\right) \tag{10}$$

With Z_i is of Normal Standard random variable. N_i is Normal random variable with parameter (a, b); $a = (\Delta t - \lambda\Delta t)\beta$; $b = \Delta t\delta$; Δt is changing time; λ is jump intensity; μ is return mean; σ is volatility; δ is the standard of deviation of jump; and β is jump mean.

Expected value and confidence interval of prediction result on Jump Diffusion Model

Suppose that $\hat{S}(t_i)$ be predicted value at period t_i. The expected value of $\hat{S}_t$ is defined as:

$$E\left(\hat{S}(t_i)\right) = E\left(\hat{S}(t_{i-1})\exp\left(\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2 - \hat{\lambda}\right) + (\hat{\sigma}Z_{i-1}) + N_i\right)\right)$$

$$E\left(S(t_{i-1})\exp\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2 - \hat{\lambda}\right)\right)E(\exp(\hat{\sigma}Z_{i-1}))E(\exp(N_i)) \tag{11}$$

Since Z_{i-1} ~ Normal (0,1), then $E(\exp(\hat{\sigma}Z_{i-1}))$ = $\exp\left(\frac{1}{2}\hat{\sigma}^2\right)$. N_i ~ Normal $((\Delta t - \Delta t\lambda)\beta, \Delta t\delta)$, so $E(\exp(N_i))$ = $\exp\left(\frac{(\Delta t - \Delta t\lambda)\beta + (\Delta t\delta)^2}{2}\right)$, we get the formula of expected value for $\hat{S}(t_i)$:

$$E\left(\hat{S}(t_i)\right) = S(t_{i-1})\exp\left(\hat{\mu} - \frac{1}{2}\hat{\sigma}^2\right)\exp\left(\frac{1}{2}\hat{\sigma}^2\right)\exp\left(\frac{(\Delta t - \Delta t\lambda)\beta + (\Delta t\delta)^2}{2}\right)$$

$$= S(t_{i-1})\exp(\hat{\mu})\exp\left(\frac{(\Delta t - \Delta t\lambda)\beta + (\Delta t\delta)^2}{2}\right) \tag{12}$$

2.2. Prediction Accuracy Measurement

In each stochastic model that is used to estimate the value in the future period, accuracy is one of the references to assess whether this model is feasible to use. We often find conditions where in the stochastic model each model parameter is significant and the model meets all the required assumptions. But when the prediction results are compared with the actual value, the prediction results are less accurate, this is indicated by the difference in the value that is quite far between the actual and prediction value. Therefore, it is important for us to measure predictive accuracy, a stochastic model that is feasible to use must have a high accuracy value (Nayak et al., 2016). In this study, prediction accuracy will be measured by Mean Absolute Percentage Error (MAPE). The equation to get MAPE according to Angelaccio (2019) is as follows:

$$MAPE = \frac{\sum_{p=1}^{n}\left|\frac{Y_p - F_p}{Y_p}\right|}{n} \times 100\% \tag{13}$$

where, Y_p is actual value at time to p, F_p, is forecast value at time p, n is number of observations. The MAPE was used as the primary metric for forecast accuracy assessment, as it is ideal for assessing large volumes of data because of its scale sensitivity, and associated ease of comparison thereof (Basson et al., 2019).

2.3. Risk Measure

The risk of loss is a major problem that often causes an investment activity to be difficult to develop until it experiences bankruptcy. Value at Risk and Expected Shortfall are the most frequently used risk measures in the financial sector. However, each of these risk measures has a drawback, the VaR model does not meet the axiom of subadditivity, so VaR is not a coherent risk measure. Then, the drawback of ES is that this model provides biased risk prediction results if there are outlier values in the data. Jadhav et et al. (2013) suggest Adjusted Expected Shortfall (Adj-ES) as an improvement of the VaR and ES models. The definition of Adj-ES is:

Definition 1 (Jadhav et al., 2013) *For every random variable X, $X, \alpha\, \epsilon (0,1)$, and $c\, \epsilon (0,0.1)$, Adj-ES on the confidence level of α, denoted $Adj{-}ES_{\alpha,c}(X)$, is the average loss value that is in the interval VaR$_\alpha$(X) and $VaR_{\alpha+(1-\alpha)^{1+c}}(X)$, is the average value of losses that are in int so the equation is as follows:*

$$Adj{-}ES_{\alpha,c}(X) = \mathrm{E}\left[X \middle| -\mathrm{VaR}_{\alpha+(1-\alpha^c)}(X) \geq -X \geq -\mathrm{VaR}_\alpha(X)\right] \tag{14}$$

with the level of confidence is $100(1-\alpha^{1+c})$.

If we suppose $\mathrm{VaR}_\alpha(X) = a$ and VaR$_\alpha$(X) = a and $\mathrm{VaR}_{\alpha+(1-\alpha^c)}(X) = b$, then by utilizing equation (12) we will obtain the equation of the Adj-ES model as follows:

$$Adj{-}ES_{\alpha,c}(X) = -\frac{1}{P(-b \geq -X \geq -a)} \int_b^a x\, f(x)\, dx = -\frac{1}{(\alpha)^{1+c}} \int_b^a x\, f(x)\, dx \tag{15}$$

By substituting $F_X(x) = \mu$, $x = F_X^{-1}(\mu)$, and $dx = d\mu$, then the final equation for the $Adj{-}ES_{\alpha,c}(X)$ model is:

$$Adj{-}ES_{\alpha,c}(X) = \frac{1}{(\alpha)^{1+c}} \int_{\alpha(1-\alpha^c)}^{\alpha} F_X^{-1}(\mu)\, d\mu \tag{16}$$

2.4. Adj-ES Model Estimation with Historical Simulation Approach

Suppose X is a random variable that denote the stock price index return, with its realized value from period 1 to t is $x_1, x_2, \dots, x_t$. Then arranged $x_{(k)1,} x_{(k)2,} \dots, x_{(k)t,}$ as returns sorted in ascending order. The formula for the Adj-ES model with a historical simulation approach for the random variable X is defined:

$$Adj{-}ES_{\alpha,c}(X) = -\frac{1}{[u]+2} \sum_{i=0}^{[u]+1} X_{(k)i} \tag{17}$$

Where $u = n\alpha^{1+c}$; $[r]$: the largest integer whose value is $\leq r$; u: the largest integer whose value is $\leq r$; $(k)i = \left[(n+1)\alpha'_{(i)}\right]$; $\alpha'_{(i)} = \alpha - \frac{i\,\alpha}{[n\alpha]+1}$; $i = 1, 2, \dots, ([n\alpha^{1+c}] + 1)$; c: real number between 0 and 0.1

3. MATERIAL AND METHOD

3.1. Data and Source

In this study, we use JKSE historical price (IDR) data during 01/08/21 to 31/08/22. Total amount of historical price are 264 data. The data that is used in this study was obtained from the website https://finance.yahoo.com/. Before making price predictions and loss risk, the discussion will begin with an analysis of price movements through time series plots and descriptive analysis. All functions of the package use R Version 4.1.0 (R Core Team, 2021).

3.2. Analysis Steps

The procedure for modeling the JKSE value through the stochastic model and predicting the risk of loss with Adj-ES risk measure is as follows:

1. Collected JKSE historical price at a predetermined time period
2. Divide the data into 2 groups: in sample and out sample

3. Measuring JKSE returns on in-sample data
4. Perform stationarity test on in-sample return data
5. Perform normality test with KS-test on in-sample return data
6. If the data is normally distributed and there is no indication of heavy tail, then the model chosen for JKSE prediction is GBM. However, if the data is normally distributed with an indication of heavy tail, then the model used is Jump Diffusion
7. Define the model parameters to build the GBM or Jump Diffusion Model
8. Predict the JKSE value with the number of prediction periods as long as the data is out of sample
9. Testing the accuracy of the price index prediction results by referring to the MAPE value
10. Measuring the risk of loss in the out-sample period using the Adj-ES model with historical simulation approach

4. RESULTS AND DISCUSSION

This analysis aims to obtain preliminary information about the characteristics of the data during the observation period. Figure 1 shows the time series plots of JKSE historical price.

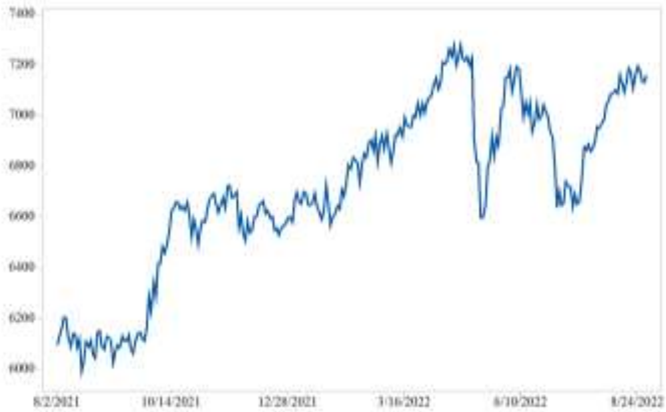

Figure 1. Time Series Plots of JKSE Historical Price (IDR)

Referring to Figure 1, during the observation period there were fluctuations in JKSE price movements. The price increase is greater than the price decrease. So, the price at the end of the observation period is greater than the beginning of the period. However, in June and July 2022 there was a significant price decreasing. Furthermore, more detailed characteristics regarding JKSE prices can be obtained from descriptive statistics value.

Table 1. Descriptive Statistics of JKSE Historical Price

N	Min	Max	Mean	Std.dev	Skew	Kurtosis
264	5992.32	7276.19	6713.999	337.6789	-0.44518	-0.6164

The average price of JKSE in the observation period is IDR 6713.99. This value has increased significantly when compared to the average value of JKSE at the peak of the COVID-19 pandemic in 2020, which at that time the average value was IDR 5248.97. Furthermore, the lowest price recorded in the observation period was IDR 5992.32, this value was IDR 1283.87 different from the highest price of 7276.19. The negative value of JKSE skewness shows that the data tends to converge on the left side of the average value. The last, with kurtosis worth less than ±3, means that there is no indication of heavy tail in the JKSE price data.

After doing descriptive analysis, then we divide the data into 2 blocks, in-sample, and out-sample data. In this study, 244 data are selected as in-sample (08/01/21 to 08/01/22) and the remaining 20 data as out-sample (08/02/22 to 08/30/22). Table 2 shows descriptive statistics of in-sample return.

Table 2. Descriptive Statistics JKSE In-sample Return

N	Min	Max	Mean	Std.dev	Skew	Kurtosis
264	-0.04515	0.02217	0.00061	0.00841	-0.83941	3.59618

In the in-sample period, the maximum recorded profit on stock investment in IDX Indonesia was 0.02217 (2.217%), while the largest loss was recorded at 4.515%. The average return that has a positive value indicates that in this period, in general, stock investment in IDX Indonesia is more dominant in recording profits than losses. A kurtosis value greater than 3 means that the in-sample return is heavy tail, meaning that there is data in the extreme value category.

Stationarity and Normality Test

This test aims to test whether the return data is stationary in the mean and meets the assumption of normality and will be done with the Augmented Dickey Fuller test and the Kolmogoorv-Sminrnov test. Stationarity test results are given in the Table 3.

Table 3. ADF Test Result of JKSE In-sample Return

Variable	t-statistics	Prob
JKSE In-sample Return	-17.28	0.00005

In this study, we choose $\alpha = 5\%$ as significance level. H_0 the ADF test is that there is a unit root in the data (data is not stationary), with reference to table 3, then the result of this test is to reject H_0 because Prob (0.00005) < α. So, we get conclusion that the data is stationary in the mean. Furthermore, the results of the Kolmogorov-Smirnov normality test are attached in Table 4.

Table 4. Normality Test Result of JKSE In-sample Return

Variable	KS-value	Sig
JKSE In-sample Return	0.054	0.085

Based on Table 4 and by setting $\alpha = 5\%$ we can conclude that the in-sample return data is normally distributed because Sig (0.085) > α (0.05). Referring to the kurtosis value, there are indications that there are outliers in the data. Therefore, in predicting the value of the price index, the GBM and Jump Diffusion models will be used. Eventually, the best model will be determined based on the MAPE accuracy test results.

JKSE Price Forecast with Geometric Brownian Motion Model

Since JKSE in-sample return has fulfill normality assumption, then the GBM model can be used to predict the JKSE price. The GBM model is composed of two parameters, namely and as drift and diffusion coefficient. The estimation results for these parameters are shown in Table 5.

Table 5. Parameter Estimates for GBM Model

Variable	μ	σ	Δt
JKSE In-sample Return	0.000362	0.008803	1 day

In addition, table 5 lists Δt which is the time change in the JKSE price prediction. We choose Δt 1 and 2 days. The consideration of choosing a short time change is due to the nature of stock prices that can experience rapid price changes in short time intervals. So, when making price predictions, the shorter the change in time used, the better. Based on Table 5, the GBM model formed for the JKSE price is

$$S(t_i) = S(t_{i-1}) \exp\left(\left(0.000362 - \tfrac{1}{2}0.008803^2\right) + 0.008803\, Z_i\right)$$

Furthermore, this model is used to predict the JKSE price for the out-sample period (20 days). The prediction results are attached in the Table 6.

Table 6. JKSE Prediction Results using GBM Model

Date	JKSE Price		Date	JKSE Price		Date	JKSE Price	
	Actual	Forecast		Actual	Forecast		Actual	Forecast
8/2/2022	6988.16	7018.79	8/11/2022	7160.38	7276.787	8/23/2022	7163.27	7465.47
8/3/2022	7046.63	7097.89	8/12/2022	7129.28	7274.348	8/24/2022	7194.71	7444.03
8/4/2022	7057.35	7288.70	8/15/2022	7093.28	7338.861	8/25/2022	7174.21	7437.66
8/5/2022	7084.65	7298.54	8/16/2022	7133.45	7414.057	8/26/2022	7135.25	7392.13
8/8/2022	7086.85	7250.00	8/18/2022	7186.56	7492.532	8/29/2022	7132.04	7343.83
8/9/2022	7102.88	7264.94	8/19/2022	7172.43	7359.635	8/30/2022	7159.47	7337.41
8/10/2022	7086.24	7262.24	8/22/2022	7107.98	7468.635			

The result on Table 6 shows that in the out-sample period the GBM model provides a predictive value close to the actual price. This shows that the GBM model can predict accurately. The MAPE value obtained for the GBM model is 2.90%, meaning that the prediction results from this model are very accurate.

JKSE Price Forecast with Jump Diffusion

In the normality assumption test, the results obtained indicate that the return data distribution function curve is leptokurtic, meaning that there are data that are outliers. Therefore, we need a Jump Diffusion model to predict the JKSE price because this model can model normal data containing outliers. The first step is to determine the Peak Over Threshold (POT). In this study, POT was determined at 5% of the total data. The quantile values selected as the threshold are -0.01621 (lower threshold quantile) and 0.0170 (upper threshold quantile). The Jump Diffusion model is composed of 4 parameters, Table 7 presents the parameter values obtained based on the in-sample return data.

Table 7. Jump Diffusion Model Parameters

	Return Mean (μ)	Return Volatility (σ)	Jump Intensity (λ)	St.dev of Jump (δ)	Jump Mean (β)	a	b
JKSE	0.000362	0.008803	-0.00314	0.00612	0.01051	0.0105	0.00612

$b = \Delta t \delta$; Δt is changing time; λ is jump intensity; μ is return mean; σ is volatility; δ is the standard of deviation of jump; and β is jump mean. Based on Table 7, we get the Jump Diffusion model equation for JKSE price with Δt = 1 day:

$$S(t_i) = S(t_{i-1}) \exp\left(\left(0.000362 - \frac{1}{2}0.0088^2 + 0.00314\right)(1) + \left(0.0088 Z_{i-1}\sqrt{1}\right) + N_i\right)$$

Where, $N \sim$Normal (0.0105,0.00612) and $N \sim$Normal (0,1). Furthermore, this model is used to predict the JKSE price for the out-sample period (20 days). The prediction results are attached in the Table 8.

Table 8. JKSE Prediction Results using GBM Model

Date	JKSE Price		Date	JKSE Price		Date	JKSE Price	
	Actual	Forecast		Actual	Forecast		Actual	Forecast
8/2/22	6988.16	6883.71	8/11/22	7160.38	7160.58	8/23/22	7163.27	7097.51
8/3/22	7046.63	6930.51	8/12/22	7129.28	7127.99	8/24/22	7194.71	7182.44
8/4/22	7057.35	6874.03	8/15/22	7093.28	7088.02	8/25/22	7174.21	7079.29
8/5/22	7084.65	6824.58	8/16/22	7133.45	7230.61	8/26/22	7135.25	7130.3
8/8/22	7086.85	6996.78	8/18/22	7186.56	7235.42	8/29/22	7132.04	7228.99
8/9/22	7102.88	7032.92	8/19/22	7172.43	7097.32	8/30/22	7159.47	7312.12
8/10/22	7086.24	7112.16	8/22/22	7107.98	7143.71			

The result from Table 8 shows that on out-sample period, The Jump Diffusion model provides a predictive value that is close to the actual price. In other words, it is proven that this model could forecast the value of JKSE accurately. The MAPE value obtained for the GBM model is 1.08%, meaning that the prediction results from this model are very accurate. Based on the MAPE value, it can be concluded that the best model is Jump Diffusion. Therefore, it is recommended that this model be used as a reference to determine price predictions and risk of loss from the JKSE index.

Loss Risk Forecast using Adjusted Expected Shortfall

Risk prediction is useful as a reference in preparing the right risk management strategy. After the JKSE price prediction is obtained in the out-sample period, the data will be used as a reference to calculate the prediction of losses in the 5 periods after the out-sample date. When there is a jump effect on JKSE data, the best model chosen is Adj-ES. Risk measurement with Adj-ES begins with determining the constant c. In this study, it was determined c = 0.5 which refers to Trimono et al. (2019). Using the Historical Simulation approach, here are the results of the prediction of the risk of loss for 09/01/22 to 09/05/22 (5 period after out sample date).

Table 9. Loss Risk Prediction using Adj-ES Risk Measure

Date	Confidence level				
	90%	95%	97%	98%	99%
09/01/22	-0.01810	-0.02978	-0.0302	-0.0302	-0.03030
09/02/22	-0.01897	-0.03057	-0.03107	-0.03107	-0.03117
09/03/22	-0.01984	-0.03144	-0.03194	-0.03194	-0.03204
09/04/22	-0.02071	-0.03231	-0.03281	-0.03281	-0.03291
09/05/22	-0.02158	-0.03318	-0.03368	-0.03368	-0.03378

On 09/01/22, at 95% confidence level, Adj-ES provides a risk prediction of -0.02978. It means that, the risk of loss that will be received by stock investors in IDX Indonesia is estimated at 2.978% of the total invested funds.

5. CONCLUSION

Based on the analysis that has been done, the JKSE return data in the in-sample period is normally distributed and there are outlier data. So, based on this condition, the

GBM and Jump Diffusion models can be used to predict the JKSE price index. Both models have very good prediction accuracy. The MAPE for each model is 2.90% and 1.08%. Because Jump Diffusion has a smaller MAPE value than GBM, we recommend the Jump Diffusion model to be used as a predictive model. Furthermore, the predicted price on the out-sample date is used to predict the risk of loss for the next five periods after the out-sample date. At the 95% confidence level, the predicted loss is -0.02978. This means that the possible loss that will be received by stock investors in IDX Indonesia is estimated at 2.978% of the total invested funds.

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