Decision Science Letters 12 (2023) 107–116

Contents lists available at GrowingScience

Decision Science Letters

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Decision-making model to predict auto-rejection: An implementation of ARIMA for accurate forecasting of stock price volatility during the Covid-19

Suripto[a*]

[a]*Lampung University, Indonesia*

C H R O N I C L E

Article history:
Received July 2, 2022
Received in revised format:
July 30, 2022
Accepted October 6, 2022
Available online
October 6, 2022

Keywords:
Decision making
Stock price
Auto-rejection
ARIMA
Covid-19
Forecasting

A B S T R A C T

This study aims to determine an accurate forecasting model, especially an error rate of around 0, and to examine how the automatic rejection system reacts to stock price as a result of the pandemic. The statistical clustering method is used for the dataset in form of daily observations, while the sample covers the period of cases before and after COVID-19 pandemic from 02 January 2019 to 20 June 2020 at the Trinitan Minerals and Metal Company. Furthermore, the data used in the estimation are the opening and closing price of returns, which are later processed using SAS analysis tools. It is shown that the most appropriate decision-making processes are those proven to be most effective. Therefore, predicting future events based on a suitable time series model will help policymakers and strategists make decisions and develop appropriate strategic plans regarding the stock market. Meanwhile, 98% of the ARIMA (1,1,1) is a forecasting model which can be applied to predict stock prices. The new approach of this study is an integrated autoregressive moving average used as an attempt to accurately predict stock prices during a pandemic.

1. Introduction

The movement of stock prices which experienced a drastic decline could show that investors are in a panic situation. This is due to the invalid and fully uncertain information that causes an abnormal stock price. However, these conditions can be overcome by the stock market authority through limiting the price (price limit), and consequently bringing it back to normal. Traits and Mohamad (2020) affirmed that stock price limitation will be effective when the stock market is in a bullish condition, whereas it is less effective when the market experiences a downward trend (bearish). Also, Ma et al. (1989) examined the effect of price limits on return behavior and trading volume in the US future market. Some authors, including Ma et al. (1989), Khodavandloo and Zakaria (2013) supported the existence of daily stock price limits by referring to the fact that this system can prevent a collapse in stock prices and provide opportunities for irrational investors to slow down the re-evaluation and to rationalize their decisions to invest. Furthermore, existence of daily stock price limits can reduce the level of price volatility by minimizing over-reaction of investors towards the market. Also, proponents of the price limits system claimed that as long as this system were implemented in 1987, there might not be a capital market crisis in October 1987 (Abdelzaher & Elgiziry, 2017; Asuamah & Ohene-Manu, 2015; Hatta et al., 2018). Several Asia-Pacific financial markets have imposed price caps to reduce excessive fluctuations. Stock price behavior was examined following daily limit movements on the Shanghai Stock Exchange for 200 companies during the period 1997-2004. Subsequently, weak evidence was discovered for an overreaction in the Shanghai stock market based on price constraints. Therefore, it was concluded

* Corresponding author.
E-mail address: suriptob.1969@fisip.unila.ac.id (Suripto)

doi: 10.5267/dsl.2022.10.002

that investors do not overreact to limit activation events except in the case of a 1-day upper boundary move. Furthermore, it was concluded that the Shanghai Stock Exchange can be considered as an efficient (semistrong) market.

Studies on the South Korean stock exchange showed price limits can prevent stock movements and support the information hypothesis while some were found to be consistent with the overreaction hypothesis (Junghoon, 2016; Fama, 1989; Fariska et al., 2021). These findings showed price limit is effective in limiting the volatility of stock prices, although it was also discovered that it is ineffective in constant volatility. Further study by Juan et al. (2017) analyzed the effectiveness of price limits in China for the 2007-2012 period, where there was high volatility, and also showed stock market deregulation was needed. This study showed the Chinese stock market is not in line with Fama (1989) which does not support a price limit. This is related to study of the Malaysian stock market, where the price limit can reduce stock volatility when the price hits the upper limit and touching the lower bound found mixed results. Conversely, when the stock market is in a crisis condition, the limit will be insignificant, especially on lower price restrictions (Imtiaz & Azhar, 2020; Purwono et al., 2018; Ryu & Chae, 2021; Arif & Hasan, 2021; Rahmi, et al., 2016; Zahra et al., 2021; Ryu, 2021; Jihadi et al., 2021). This study supports the information hypothesis that price limit significantly reduces stock price volatility (Ji & Yoon, 2020; Ryu & Chae, 2020).

The movement of stock prices reflects the level of risk for investors. Therefore, there is a need for an appropriate forecasting design as a means of anticipation in reducing the level of risk. One forecasting solution that is widely used at stock prices is the (ARIMA) approach (Dritsaki & Dritsaki, 2020; Gontijo, et al., 2020; Azhar, et al., 2020; Gunarto et al., 2020; Alsaedi et al., 2019; Akhmetzhanov et al., 2018; Dritsaki, 2018; Mikhaylov, 2018; Jamalmanesh, et al., 2018). This approach is a time series forecasting model that is implemented to predict stock movements (Aktas et al., 2020; Nyangarika et al., 2019; Bakar & Rosbi, 2017). The present study contributes to the literature by finding the best ARIMA model to produce forecasting numbers, which will further be the basis for examining the relationship between price limits and fluctuations in stock prices. Secondly, the study aims to examine how the auto-reject system reacted to stock prices due to the unusual coronavirus disease (COVID-19) pandemic.

2. Literature review

The study of volatility model is essential for academics and practitioners in this decade (Handika & Chalid, 2018). Suspicious share volatility requires a stock price restriction policy that has the objective to limit fluctuations in share prices. Therefore, regulators impose daily stock price limits to restrict extreme movements. Price limits are often used in the stock market to prevent fluctuations in stock prices that are too fast or too much 7 (Li et al., 2014; Alomar, & Moll, 2018). Furthermore, stock market regulators form a limit as a tool to prevent price movement (Khodavandloo & Zakaria, 2013); (Pointer & Khoi, 2019; Karbowski & Prokop, 2019; Mihi-Ramírez et al., 2019; Lee et al, 2018; Laipaporn & Tongkumchum, 2018; Laipaporn & Tongkumchum, 2020; Kennedy & Nourzad, 2016; Siddiqui, et al., 2016; et al., 2019).

The limit mechanism should influence stock movement. Consequently, the movement of stocks during a pandemic tends to be uncontrollable due to irrational market sentiment. This condition is almost the same with the 1987 American crisis where Brady Report (1988) suggested a circuit breaker mechanism, such as a price limit, to prevent chaos in the market system. A price limit is a mechanism for controlling daily stock movements, therefore, share price moves between the upper or lower limits on a trading day. Furthermore, the limit aims to reduce excessive volatility due to information asymmetry. As a result of overreaction by investors due to panic, a circuit breaker mechanism is needed. This provides an opportunity for investors to make rational decisions, which in turn will reduce the movement of stock volatility. Investors are allowed to think rationally, hence the stock price will move towards its intrinsic price. Fama (1989) affirmed that when the process of price formation on shares is interfered with, the volatility of stock price will increase. The implication of a restricted price movement is a shift in volatility on the next trading day. The price limit is not able to reduce volatility of stock prices, therefore will cause more instability in the days to come. Therefore, subsequent volatility in stock prices is in line with the spillover hypothesis. According to Fama (1989), when the movement of a stock price touches the upper or lower limit, price limit restricts trading on that day. This is as a result of interference that prevents the stock price from reaching its equilibrium point. When the stock price has not reached equilibrium, it will continually move towards that point. Conversely, when the limit does not make the stock price reach equilibrium on that day, the stock price will eventually reach equilibrium the next day. The existence of stock price volatility on the next day is in line with the delayed price discovery hypothesis (Hong, 2016). Fama (1989) stated that this theory is the same when a limit prevents trading on one day, it is less liquid, therefore the next trade increases significantly. This is related to an imbalance in the trading volume, hence the volatility of the shares exceeds the predetermined price, thereby significantly increasing trading volume. Several Asia-Pacific stock markets impose price limits to reduce excessive volatility. Also, a study on the Shanghai Stock Exchange for the period between 1997-2004 with 200 companies found insignificant evidence that price limits can reduce volatility. Furthermore, price limits are intended to provide opportunities for investors to obtain good information, hence creating rational decisions in the capital market. Daily stock price limit related to stock return volatility (Abdelzaher & Elgiziry, 2017; Sayed & Auret, 2018; Li et al., 2014; Upadhyaya et al., 2020; Thuy & Thuy, 2019; Soleymani et al., 2017; Siddiqui, 2016; Herwany et al., 2021) stated that limit regulations are not effective in dealing with volatility levels. According to Zhang et al. (2016), it was shown that the regulation of price limits increases volatility. Khodavandloo and Zakaria (2013) discovered that stock volatility that reaches price limits will experience volatility the next day. Price restrictions do not affect movements (Li et al., 2014). Chen et al. (2014), Abdelzaher and Elgiziry (2017), Danışoğlu and Güner (2018), Rillo (2018), Tao et al. (2017), Kristiana et al. (2021), Goh et al. (2021), Abu-lila (2021), Purwono et al. (2018) and Aktas et al. (2020) did not agree with price limit. It was assumed that the limits system causes an increase in high price volatility after the stock reaches the limit (volatility spillover hypothesis). It was also claimed that this system has influence or intervention in trading activities (trading interference hypothesis). Moreover, the existence of a limit system is considered to delay reaching equilibrium in one or several days (delayed price discovery hypothesis). Those who oppose the system of price limits assume that it causes new problems and risks in investing higher.

3. Methodology

The empirical strategy used to analyze stock price movements that have experienced a very significant decline due to the 2019 coronavirus disease (COVID-19) pandemic consists of three basic steps:

3.1. The ARIMA Model

Alsaedi et al. (2019) developed a new forecasting tool specifically known as the ARIMA model. This model is generally formulated as ARIMA (*p*, *d*, *q*), in which *p* is the order of autoregressive (AR), *d* is the difference, and *q* is the order moving average (MA). The AR model shows dependent variable is influenced by the dependent variable in the previous period (time lag of the dependent as an independent). Also, the MA model is an independent variable, and is the residual value (error) in the previous period. The AR and MA merge to produce ARIMA model, which begins with the formation of stationary data. Generally, the form model AR (*p*) can be written in the following equation:

$$SPAR_t = \beta + \theta_1 SPAR_{t-1} + \theta_2 SPAR_{t-2} + \theta_3 SPAR_{t-3} + \cdots + \theta_p SPAR_{t-p} + \varepsilon_t \tag{1}$$

MA(q) is presented as follows:

$$SPAR = \mu + \varepsilon - \lambda_1 \varepsilon_{t-1} + \lambda_2 \varepsilon_{t-2} + \lambda_3 \varepsilon_{t-3} + \lambda_q \varepsilon_{t-q}\,;\ \varepsilon_t \sim N\,(0, \theta^2) \tag{2}$$

The reason for using ARIMA is because statistical assumptions are fulfilled in the time series g data as stationary. Also, using this model aims to predict the value of past and present dependent variables to produce accurate short-term forecasts that are relevant to the pandemic.

3.2. Data Stationarity Test

Autoregressive model application has conditions that need to be met, which include using a stationary sort of data. The data are said to be stationary as long as the average value and variance do not change systematically over time, i.e, have a constant average value, variance, and covariance. Meanwhile, testing the stationarity of data can be conducted by looking at correlations (correlogram) through the autocorrelation function (ACF). Data series that have non-stationary properties are often referred to as unit root non-stationary time series (Tsay, 2005). Statistically, this ACF value should be located at −1 and 1. Furthermore, data are said to be stationary when the ACF value at each lag is equal to 0, and non-stationary when the ACF value at each lag is not equal to 0 or is relatively high (Eliyawati, 2012; Denkowska & Wanat, 2020). The augmented Dickey-Fuller (ADF) test is also used to ensure the data series is stationary. The ADF test mathematical framework can be seen as follows (Brockwell & Davis, 2002; Tsay, 2005):

$$SPARt = \mu + \gamma_1 SPAR_{t-1} + \sum_{k-1}^{p-1} \gamma_k \, \Delta SPAR_{t-1} + \varepsilon_t \tag{3}$$

where SPARt is time-series data from PURE shares that follows the AR (*p*) model with mean μ. The equation also forms γ_i as a parameter, and ε_t is white noise with mean 0 and variance, σ^2. Alongside certain considerations, the test was conducted with the condition that the statistical value τ is as follows (Virginia et al., 2018):

$H_0 = \gamma_1 = 0$ (non-stationary PURE stock data)
$H_1 = \gamma_1 < 1$ (stationary PURE stock data)

ADF test:

$$\tau = \frac{\gamma_i}{\widehat{se(\gamma_i)}} \tag{4}$$

conditions where $\tau < -2.57$ or when $P < 0.05$, subsequently, H_0 will be rejected. At the end, when the PURE share data proves to be non-stationary, a statistical step in the form of differencing the data will be conducted.

A diagnostic test was carried out to determine whether the chosen model is good according to the result of the residual test. This test was done by observing correlations (correlograms) both through the ACF and the partial ACF (PACF). Given that the ACF and PACF coefficients individually are not significant, the residuals obtained are random. Also, to determine whether the ACF and PACF coefficients are significant or not, it is seen through statistical tests developed by Ljung–Box or better known as the Ljung–Box (LB). Given that the LB value is smaller than the statistical critical value of the chi-squares distribution table, subsequently the residual is random (white noise), hence, it can be deduced that chosen model is good.

3.4. Empirical Results and Discussions

This study comprises a dataset in the form of daily observation, whereas the sample covers the case period before and after the COVID-19 pandemic from January 02, 2019, to June 20, 2020, in the Trinitan Metals and Minerals Company with the share code PURE. The data used in the estimation are the opening and closing price of the return, which were subsequently processed using the SAS analysis tool. In the ARIMA procedure, the first assumption which needs to be met is the stationary data. Also, the ADF unit root test is used to examine the time-series data stationarity. Plotting of daily PURE share price data results are presented in Fig. 1.

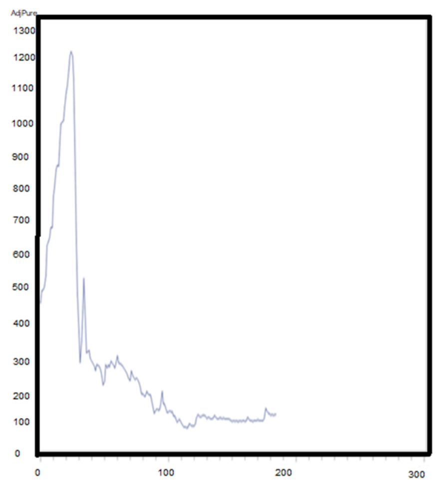

Fig. 1. Present stationary data checks

The journey of PURE stock data plotting can be easily detected. The non-stationary data is seen from visual charts with extreme volatility and sharp decrease. This condition requires the research team to examine further, hence ADF unit root tests were conducted, and shown in Table 1.

Table 1
Augmented Dickey-Fuller Unit Root Tests

Type	Lags	Rho	*Pr* < Rho	Tau	*Pr* < Tau	*F*	*Pr* > *F*
Zero Mean	3	−3.8642	0.1757	−1.5517	0.1135		
Single Mean	3	−6.2855	0.3204	−1.7577	0.4005	1.6338	0.6544
Trend	3	−14.0743	0.2072	−2.4638	0.3456	3.0509	0.5678

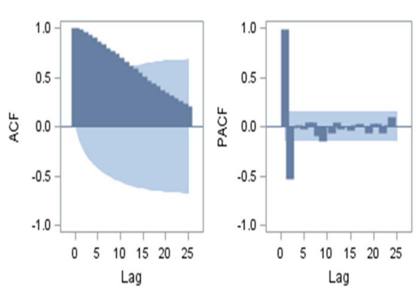

Fig. 2. Presenting PACF and ACF Graphs

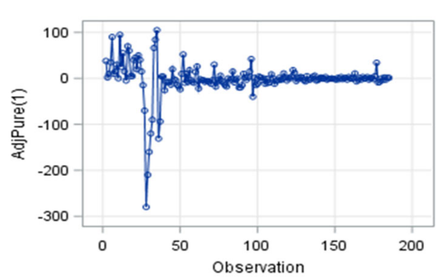

Fig. 3. Data Differentiation Results

Based on the above table, it was shown that when the *P*-value is >0.05, it gives a signal that the data used are not stationary. Furthermore, ACF and PACF charts can be a reference to data stationarity. The results of statistical processing on the PURE stock data are shown in Fig. 2. In Fig. 2, PACF and ACF showed a very slow decline and are outside the area of confidence. Therefore, it could be concluded that PURE stock data are not stationary. Statistically, non-stationary data can be conditioned to be stationary in some ways, one of which is to aim at reducing the distance of volatility between data. Because the data are not stationary, differencing treatment was conducted. As shown in Fig. 3, the average original data graph volatility has been between between 0. This is a quick method to draw the initial assumption that the PURE stock data are stationary.

Table 2
Before Covid-19

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	**0**	-1,2880	0.0622	-6.82	0.1135		
	3	-3.8642	0.0622	-1.5517	0.1135		
Single Mean	**0**	-2,0951	0.0801	-1.7577	0.4005		
	3	-6.2855	0.3204	-6.47	0.4005	1.6338	0.6544
Trend	**0**	-4,6914	0.1384	-6.80	0.3456		
	3	-14.0743	0.2072	-2.4638	0.3456	3.0509	0.5678

The PURE stock data is not stationary because the ADF test value with a P value> 0.001 is shown in Table 2. To confirm this, white noise was verified in the data. Also, the white noise figure with the overall correlation value of the data moves away from 0 in contrast to the lower lag as shown in Table 3; the white noise hypothesis in the data is acceptable.

Table 3
Indigo ADF Test After Differencing

Type	Lags	Rho	*Pr* < Rho	Tau	*Pr* < Tau	*F*	*Pr* > *F*
Zero mean	**0**	−740.553	<0.0001	−6.82	<0.0001		
	1	−847.124	<0.0001	−6.48	<0.0001		
Single mean	**0**	−742.632	0.0013	−6.82	<0.0001	23.24	0.0010
	1	−850.388	0.0013	−6.47	<0.0001	0.89931	0.0010
Trend	**0**	−742.762	0.0005	−6.80	<0.0001	23.14	0.0010
	1	−850.534	0.0005	−6.46	<0.0001	0.89236	0.0010

ADF test values with *P* values <0.001 are listed in Table 3. Therefore, the PURE stock data has been stationary using the differencing method. To verify this, white noise was examined in the data. Also, the white noise numbers with the overall correlation value of the data close to 0 in line with the higher lag are shown in Table 4; the hypothesis in the data can be rejected.

Table 4
Autocorrelation Check for White Noise

To lag	Chi-square	DF	*Pr* > ChiSq	Autocorrelations					
6	90.03.00	6	<0.0001	0.4125	0.21319	0.08056	0.029	−0.085	−0.107
12	94.46.00	12	<0.0001	−0.035	0.099	0.092	0.050	0.009	−0.026
18	105.32.00	18	<0.0001	−0.048	−0.041	−0.127	−0.146	−0.106	−0.029
24	123.62	24	<0.0001	−0.070	−0.115	−0.064	−0.078	−0.168	−0.173

Furthermore, identifying the forecasting model with ARIMA can be carried out with a higher confidence level. A one-time statistical simulation was carried out for the PURE stock data which showed an immediate good result. As shown in Table 4, the estimated value of MA (1) is −0.09796, t-test = −0.79, with *P*-value = 0.4296 < 0.05, which means the model is significant. Therefore, the ARIMA model (1,1,1) was chosen with the following estimation models:

$$Pv_t = -1.11513 - 0.09796\, PL_{t-1} + 0.53176\, \alpha_{t-1} + \alpha_t$$

Table 5
Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	*t*-Value	Approx *Pr* > |*t*|	Lag
MU	−1.11513	5.43435	−0.21	0.8376	0
MA1,1	−0.09796	0.12374	−0.79	0.4296	1
AR1,1	0.53176	0.10531	5.05	<0.0001	1

In the time series data, the estimation of heteroscedasticity is very common. In other studies, the ARCH effect was identified, and given that the hypothesis was accepted, forecasting will be conducted via the GARCH method. As shown in Table 6, there are no significant ARCH effects until the seventh test order. Therefore, the best ARIMA model in forecasting the PURE stock data was considered.

Table 6
ARCH Effect Identification

Tests for ARCH disturbances based on residuals				
Order	***Q***	***Pr* > *Q***	**LM**	***Pr* > LM**
1	1.8956	0.1686	1.6138	0.2040
2	2.9071	0.2337	2.2710	0.3213
3	5.6157	0.1319	4.1315	0.2476
4	6.2081	0.1841	4.3053	0.3663
5	18.1254	0.0028	12.8951	0.0244
6	18.5771	0.0049	12.8999	0.0447
7	21.0290	0.0037	13.9772	0.0516

As compared in Table 6, no ARCH values were found with a P-value of <0.0001, which means test orders 1 to 7 of the PURE stock data are non-heteroscedasticity. Therefore, the ARIMA model (1,1,1) was examined further. The investigation was initiated by studying the square value of 0.98 or 98%, which is a good initial signal. Furthermore, it could be calculated that the root-mean-square error, that is, 31.7, has entered into the lower class. Confidence in the model can be evaluated using the absolute error (MAE) and mean absolute percentage error (MAPE), which are in the low range of 16.6 and 6.3. Hence, ARIMA can be categorized as the best model for forecasting PAA shares.

Table 7
Statistics from the ARIMA the PURE Stock Data

Yule-Walker estimates			
SSE	181918.052	**DFE**	181
MSE	1005	**Root MSE**	31.70287
SBC	1824.20123	**AIC**	1811.31981
MAE	16.6324539	**AICC**	1811.54203
MAPE	6.31542481	**HQC**	1816.54034
Durbin–Watson	1.7421	**Transformed regression R^2**	0.0581
		Total R^2	0.9872

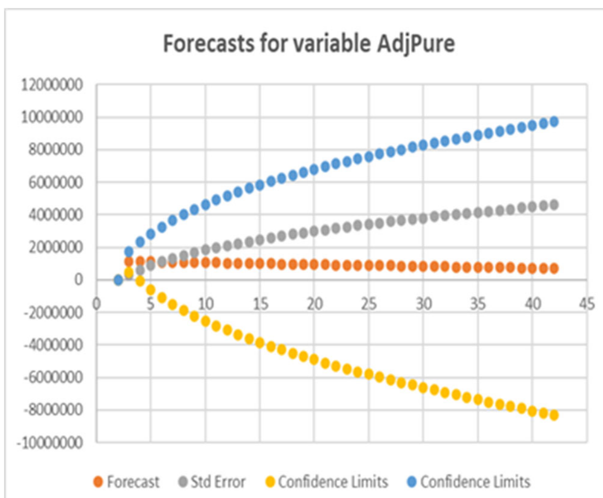

Fig. 4. Forecasting of the PURE Stock Data

Subsequently, the good results from this study, are to be followed up by the forecasting of PURE stock data with the best model. Forecasting provides an early opportunity for users and practitioners in determining economic steps. PURE stock data forecasting using the ARIMA model (1,1,1) is shown in Figure 4. In statistical conditions with a longer period, it has been shown in Figure 4 that the confidence limit range is also widening. This is evidence that the length of the forecast timespan will also provide a higher bias. In line with the confidence limit, the error rate showed an increase over time. The interesting part is the implication of PURE stock data forecast, which tends to increase stability. Also, a quick withdrawal of auto-rejection conclusion is applied to the PURE stock without disrupting its volatility. Furthermore, the level of market confidence in PURE stock remains relatively good, therefore no selling action causes the stock price not to go up.

4. Conclusions

In this study, ARIMA model was used for analysis. The impact of the COVID-19 pandemic might be unfavorable, especially on energy company shares. In fact, PURE is one of the energy companies whose shares dropped dramatically, hence it was hit by an auto-rejection policy. Also, auto-rejection can have an adverse effect due to the market panic that cannot be muted, therefore, the subsequent increase in stock prices cannot be reversed. The ARIMA model in this study is the best for forecasting PURE stock prices. These results are new, which relate to forecasting and auto rejection policies during the pandemic period. All factors considered, the most appropriate decision-making process is the one that proves to be the most effective. Moreover, predicting future events based on an appropriate time series model will help policymakers and strategists make decisions and appropriate strategic plans regarding the stock market. Consequently, 98% of ARIMA (1,1,1) is a forecasting model which can be applied to predict stock prices. Therefore, the auto-rejection policy at Trinitan Metals and Minerals Company (PT.PURE) does not interfere with volatility of the stock prices.

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